A GROUP COGNITIVE APPROACH TO OPERATIONAL RISK IDENTIFICATION AND EVALUATION

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ABSTRACT

This paper describes the *Cognitive Risk Identification and Measurement* (CRIM) framework of risk identification and measurement. A cognitive technique, based on the Delphi method which, can be employed rapidly and with limited organisational impact to identify the risks an organisation faces and assess them in terms of probability, impact and ability of the organisation to manage those risks. It also shows examples of how the results of this analysis can be presented to management for action.

BACKGROUND

Many solutions and approaches exist to manage risk. A frequent problem faced by researchers, managers and practitioners alike is comprehensive risk identification and building a consensus as to the relevant importance and probabilities of these risks.

Relying on external expertise alone does not take into consideration the unique operational risks that exist because of the operational procedures and organisational structure of a given organisation.

In particular there are challenges relating to achieving complete coverage of all risks and ensuring the importance of risks is agreed and recognised. This is complicated by additional challenges of organisational and group behaviours, such as "Group think" and the roles of dominant individuals, which can place a strong bias on any risk evaluation process.

CONTENT

This paper describes these and other challenges faced by the author whilst conducting risk research in a major investment bank. These include:

- Group dynamics
- Organisational impact of research
- Timing considerations
- Involving outside "experts"
- Dominant individual behaviours
- Decision making techniques and their impact, such as availability theory, and prospect theory.

It shows how cognitive techniques can be employed to overcome many of the issues faced by group methods, using a technique, developed from the Delphi method. The paper shows how this technique can be used in practice and how the results can be analysed and presented to decision makers.

COGNITIVE RISK IDENTIFICATION AND MEASUREMENT (CRIM)

This paper is primarily a description of a cognitive process which I call the *Cognitive Risk Identification and Measurement* (CRIM) framework. This was developed as part of doctorial research conducted by the author at Cranfield University in the UK. As such this paper is a description of the method developed and so is methodological. A paper describing the findings and their impact is also available entitled "Group risk behaviour in unfamiliar problem domains". The method is important because it provides a practical approach to identifying and prioritising risks.

The amount of regulatory and management attention donated to operational risk is increasing. While regulators are focusing greater attention on the operational risk they are not prescriptive. This means that organisations are free to apply the solution of choice to the problem.

There are a number of risk management frameworks. These frameworks generally fail to address the question of risk identification and risk assessment. That is to say the organisation needs to be aware of the risks and be able to evaluate them. Some organisations may take an approach of benchmarking and then examining the gaps, this approach may not be complete. Organisations face risks that result from their unique situation and this would not be addressed by a benchmarking approach.

To address this need CRIM was developed. CRIM aims to combine takes industry best practice, the company's documentation, where available, and the organisation's knowledge to produce a more complete set of risks. It then uses the organisations knowledge and experience to perform an initial assessment of these risks and how well the organisation can address them. This approach also has the advantage of being possible to implement quickly (typically 4 weeks) and with little impact on the organisation (typically 2-3 hours per participant, 12-15 participants). In practice it has proved a valuable contribution to initiating risk management projects, and assessing project risk.

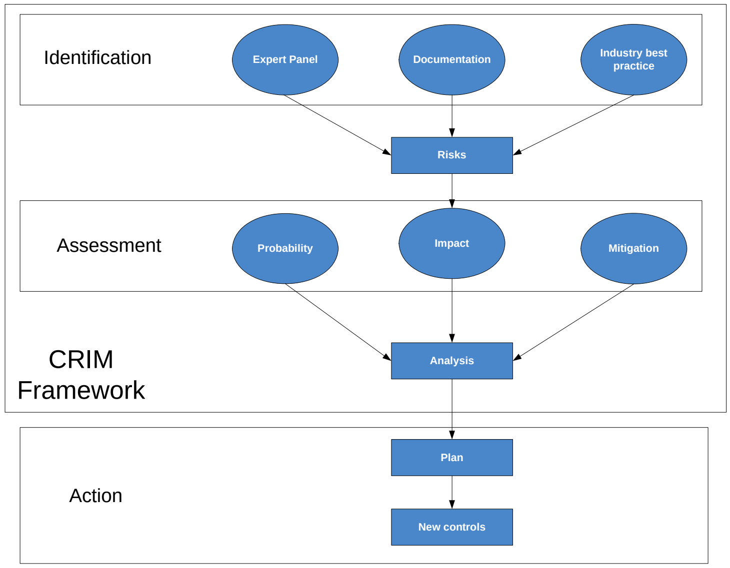

Figure 1 - CRIM Framework and risk management

THE CONTEXT OF THIS RESEARCH

CRIM has been used in various situations such as pre and post acquisition risk analysis, business development and project delivery risk analysis. The paper will draw examples from research into a large scale bank acquisition. The sample data shown is taken from that risk review.

Banks are no strangers to Merger and Acquisition (M&A) behaviour; they are frequently involved in M&A activities on behalf of their clients. This activity usually takes the form of financial involvement only (organising finance, valuing company assets and so forth). The context here is somewhat different; the bank is directly making an acquisition on its own behalf. As such it is involved directly in all aspects of the M&A process. This places the organisation outside its normal, and therefore "familiar", operational domain. This automatically presents new inherent risks. If the organisation is doing something different from the normal then it will not have the experience it would enjoy for everyday activities. This results in either normal controls being used in circumstances they were not designed to operate in or they will need to be modified or replaced.

A special challenge is the process of changing the legal ownership of the company (Change of Control). This is a highly regulated area and as such places constraints upon all organisations, and in the case of investment banks there are additional constraints which are unique to the financial services industry. This is because the basic legislation relating to mergers and acquisitions forces firms to take an "arms length" approach to the process prior to the change of control. Financial regulators request that there be sufficient integration of controls to ensure there is single regulatory reporting from the moment of the change of control. This therefore places the two companies very closely together, at the same time they are required to be "arms length". The focus is primarily on the risk identification and behaviour during the acquisition's Change of Control (CoC).

Research and business experience shows that M&A activity is both expensive to undertake and also failure-intensive. Most M&A transactions do not achieve their stated aims (Meeks, 1977). M&A failures are very expensive in terms of shareholder value and can even threaten the very existence of the organisation. A recent example of this is the post-merger losses of US$97 billion at AOL Time Warner (Thal Larsen, 2003).

As indicated earlier, banking and finance M&As are subject to special regulatory reporting requirements which require close co-operation between the acquirer and the acquired, which is normally prohibited and therefore normally not an operational consideration prior to the CoC.

With such high probability of loss combined with such high potential loss, risk management is very important in these circumstances. This has been given greater importance in recent years by a number of regulators and other stakeholders, looking to improve financial reliability, governance and reporting. High-profile corporate failures and reporting scandals such as those involving Enron/Arthur Andersen and WorldCom (Larkin and Casscles, 2003) have added impetus to the drive for greater corporate reliability.

ORIGINAL RESEARCH QUESTION AND DESIGN

As mentioned earlier when this method was developed it was in support of research which was undertaken to answer a number of questions:

1. What risks did the organisation face?
2. What were the relative probabilities of each risk occurring?
3. What were the relative impact of each risk, if they should occur?
4. How well prepared is the organisation to address or mitigate these risks should they occur?

The bank had successfully completed one acquisition and was about to undertake another. It wanted to understand its risk profile in this situation so that it might be able to take preventative action when approaching the upcoming acquisition.

CHALLENGES AND CONSIDERED TECHNIQUES

This section describes various approaches and methods that were considered to answer the original research questions. It also describes the rationale for selection and rejection, which ultimately led to the creation of CRIM. The objective of the project was to identify risks and quantify their significance (probability and impact) and their mitigation (the degree to which the organisation has either eliminated the risk or taken action to mitigate its impact.). Because of this a method would ultimately be required which would answer these questions in a quantitative manner. It is also necessary to be able to analyse the risks in terms of their timing, and classify their nature. The information available came from three sources; industry practice (attained by using an outside expert in M&A activity), company records and a small pool of professionals who were familiar with the organisation and challenge it was facing.

INITIAL APPROACHES CONSIDERED FOR THE RESEARCH

Appropriate methods that could be considered for the research were required. The starting point was to review *Doing Quantitative Research in the Social Sciences* (Black, 1999) and *Qualitative Data Analysis* (Miles and Huberman, 1994) to inform and to provide an overview of the options that one could consider. These methods had to work with the constraints of the data sources available, the limited time (because of the need to prepare for the next acquisition) and objectives of the research. Black (1999) proposes a process for hypothesis which was not appropriate for this research, since the objective was to identify and measure and not propose a hypothesis. However, he also outlined approaches to data gathering which can be used. The selected method needed to be appropriate for post-facto investigation, based on three broad approaches which can be identified;

- The first approach would be to review the company records (from the first acquisition) and identify the risk to the merger's success documented in the company's records. This could then be followed by producing a questionnaire which could be used to poll the panel of experts. This approach benefited from the ease with which it could be "operationalised", provided that there was a way to manage the volume of data in the company records. A significant downside with this approach is that it would not gather data from the experts and so miss the benefit of their experience. Also, a questionnaire might not be interpreted in the same way by all respondents. In addition, there is also no real scope for follow-up with this approach. Because of these concerns the approach was discounted.
- The second approach considered was to interview the panel of experts. Analysis of the transcripts of these interviews using content analysis (or a similar analysis) extract the risks identified and produce a questionnaire which the panel could complete. This offers many benefits because it would base the work on the experts' opinion and so include their input. They would be able to incorporate whatever they wished, and as it is based on the interview; it could be structured it to bring greater focus on the change of control part of the merger (the primary focus of the research). In spite of the advantages of this approach, there were also concerns. There could be ambiguity in the results returned by the experts, and in addition, there could be disagreement over the answers without the opportunity to address these.
- A third approach would be to organise a workshop or focus group session with the experts. This offers the possibility of the experts getting into a detailed discussion and debate relating to the central issues, which

presents great scope to arrive at an agreement and to elicit greater depth in relation to understanding the risks present. Such a focus group would be challenging to run as there would be many participants from different organisational levels involved. It would need to be managed and directed appropriately so as to cover all the issues in a reasonable time frame. An additional logistic challenge would be scheduling a time and venue agreeable to all of the parties. Even if this could be achieved the possibility exists that the group could be dominated by a small number of individuals, a common problem with group discussions (Fourlis, 1976; Jenkins and Thoele, 1991).

The second approach, while attractive from an operational and data quality perspective, still suffered from the possibility of there being disagreement on the relative importance of risks. This makes it harder for management commitment to address the risks from within the organisation if there is a perception of disagreement as to the importance of these risks. To solve this the basic approach is altered so as to incorporate a variation of the Delphi forecasting method. This would allow the respondents to answer the question more than once, and thus modify their answers once they became aware of the answers of the others in their group.

While popular in the commercial world, the Delphi method is not widespread in academic research (Fourlis, 1976), partly because it is usually used as a forecasting tool (Helmer, 1968; Dalkey, 1969), and partly because some academics are not comfortable with it as a rigorous research tool (Fourlis, 1976; Jenkins and Thoele, 1991).

THE DELPHI METHOD

The Delphi method developed as a group consensus technique to produce forecasts for a particular topic or area of interest (Hiltz and Turoff, 2001). It was developed by Olaf Helmer and Norman Dalkey at the Rand Corporation during the 1960's (Helmer, 1968; Dalkey, 1969).

Its popularity has grown substantially in terms of frequency of use and purpose for which it is applied. It is applied to a wide range of forecasting activities across various industries (Jenkins and Thoele, 1991). It has been found to be more appropriate than numerical forecasting methods in many circumstances (Fourlis, 1976). Fourlis found that successful use of the Delphi method depends upon:

- Anonymity of the members of the panel – the panel would be unaware of the identity of any other panellist, so as not to influence their opinion.
- Controlled feedback – the panel make their estimates (give their opinion) in a uniform way.
- Statistical group response – the opinions are weighted in some manner. This would depend on the topic, such as favouring the views of recognised specialists, or those with long experience.

One of the benefits of the Delphi method is the fact that it is asynchronous. Some consider this to be a prerequisite (Hiltz and Turoff, 2001), partly because of the use of mail to co-ordinate and correspond with the members of the panel. Today, we can use technologies to support us to work in a more iterative fashion, if desired. When Helmer was describing the Delphi method in the late 1960s, he made no specific reference to this, in fact, he described the process as a series of sequential steps.

This is not the first time the use of the Delphi method has been extended beyond forecasting. It is frequently used as a "decision support" tool (Hiltz and Turoff, 2001), though there is no indication that this was Helmer's original intention.

The use of the Delphi method as the core of this research method was because of the consensus-building nature of the method. Using it facilitates the formation of consensus about the risks, their significance and the ability of the organisation to mitigate them.

A further advantage of the Delphi method is that it offers the potential to achieve higher quality decision-making. In the late 1960s research into the issue of the quality of decision-making was conducted within the Rand Corporation (Dalkey, 1969). The conclusion was that the lack of a "face-to-face" procedure and the anonymity of the Delphi method results in a better quality of decision-making, thus resulting in a better consensus.

Jenkins and Thoele (1991) also identified the potential for better quality decision making within the group decision-making process. Further support for the accuracy of group forecasting compared to that of individuals is found in Sniezek (Health & Safety Executive, 1989).

Interestingly Jenkins and Thoele also point out that sometimes a group of experts was not significantly better at forecasting than the general public, citing an example from Wright and Schaal (1988) relating to the quality of decision-making, in terms of the selection of high performing equities between the general public and experts.

The process also allowed for better learning. By going through multiple iterations of the opinions of various stakeholders, it was possible for each to gain an appreciation and understanding of the knowledge, issues and perspective of the others. Mandanis (1968) found that "the Delphi method can take the form of a detailed understanding by corporate executives of the reasoning that underlies their respective staff's recommendations, or it can help the latter appreciate more intimately, the biases and style of those they counsel".

There are two great dangers with group decision making. The first is the existence of group think (Janis 1972). The Delphi method does not necessarily mitigate against this, but it is less likely to produce the conditions under which groupthink can exist. The second danger of group decision-making is the impact of a dominant individual (Jenkins and Thoele, 1991). The anonymity of the Delphi method avoids contact between participants - this eliminates the impact of dominant individual behaviour. There is no threat of a single individual "setting the direction" or intimidating others and preventing them from taking part, as there is no group interaction.

Other researches have identified weaknesses with the Delphi method. Fourlis (1976) identifies and addresses a number of these, namely;

- Panel selection - the members of the panel need to be deemed to be "experts". Those selected for the panel are all experts in that they have either considerable professional or academic expertise of the subject area. Of course, some experts can have a greater degree of expertise on some aspects of the issue than others. It is possible to allow participants to assign a self-weight to the questions if necessary.
- Group size - like any sampling method, the error decreases as the sample size increases. Group sizes of 13 to 15 are optimal (Dalkey, 1969). This is possibly a reflection of the technology used at the time. Today, using interactive technologies, it is possible to have any number of experts take part. No research has been undertaken to determine whether or not this is the case.
- The questionnaire - this needs to be clear to the respondent, in that they must be clear as to the questions being asked of them. Because of this, it may be necessary to provide the participants with extra background knowledge.
- Reliability of the technique - the conclusion that Fourlis (1976) comes to, and quotes a number of sources to support him, is that the method is reliable when used in the right context. The sort of economic and academic value placed on the findings of Delphi studies by commercial organisations also supports this. An example of this is the recent Delphi-X study (Flynn and Belzowski, 1999) which examines trends within the petroleum industry. Fourlis also concludes that there are a number of potential issues relating to the respondents' interpretation of the questions that in turn bring into question the researcher's ability to compare answers. There are also issues that surround other group techniques, such as polling. Therefore, we should conclude that the issue relates to the application of the technique, rather than to the technique itself.

The method of qualitative data collection selected was adapted from the Delphi method. This process started off initially as a series of interviews. In order to draw these interviews together, the process described below was followed.

The need for an expert panel for the Delphi method required people who had played an important role in one of the mergers. They were broadly categorised as consultants, managers, senior managers, staff and external specialists. Appropriate individuals who would fit the criteria were identified. In practice, there was not 100% participation as can be seen in Table 6 - Delphi participation.

TECHNIQUE DEVELOPED

This section describes the method developed. The method is the result of the research constraints and the viability of other research methods in addressing the needs of identifying risks, agreeing their relative significance and how well the organisation is able to mitigate them.

PANEL SELECTION

A "panel of experts" was formed. A list of people who had worked on the previous acquisition at various organisational levels, but in positions that were sufficiently central to allow them have a cross-organisational view of the acquisition (as was the scope of the research). Over twenty potential participants were identified. These were classified into a number of categories based on their role. These were external consultants, managers, senior (top team) managers and central staff. A panel size of 15 was selected because it was possible that there would not be 100% participation, and this is the "high end" of the optimum panel size. Panel members were selected by their areas and business unit to elicit as wide a group of responses as possible. The panel was balanced in terms of representation from each group. The method of qualitative data collection is based around the Delphi method. For it to be effective a body of individuals with expertise and knowledge of the merger being studied was required. The people needed to have worked in areas where they would have been exposed to a wide range of issues, and thus not bias the data in any particular direction. To reduce the possibility of bias resulting from a homogeneous panel, a cross-section of participants was drawn from different levels within the organisation, including external resources. All of the external resources were consultants who had worked on the acquisition. In addition an external member who had not worked on the acquisition, but who is a leading academic and business consultant, and is generally considered to be one of the UK's experts on mergers and acquisitions was also included. His input was included because he could bring a wider perspective than merely this particular acquisition. All the members of the panel were approached and agreed to take part. In total two iterations of the questionnaire were circulated; these are referred to as Delphi 1 and Delphi 2. Not all panel members took part at every stage of the process. In practice only 12 contributed, the actual level of participation is shown in the table below.

Area	***Interview***	***Delphi 1***	***Delphi 2***
Consultant 1	Yes	Yes	Yes
Consultant 2	Yes	Yes	No
Consultant 3	Yes	Yes	No

Manager 1	No	No	Yes
Manager 2	Yes	Yes	Yes
Manager 3	No	Yes	No
Senior Manager 1	No	Yes	No
Senior Manager 2	Yes	No	Yes
Specialist 1	Yes	No	No
Staff 1	Yes	Yes	Yes
Staff 2	Yes	Yes	Yes
Staff 3	Yes	Yes	Yes

Table 1 - Delphi participation

INTERVIEWS

Two semi-structured pilot interviews were conducted. The basic structure of the interview was:

- Introduction
- Explain the research in general terms
- Explain its goals
- Explain the method of research
- Ask the interviewee to describe their position at the time of the merger
- Conduct the interview by asking a series of questions, prompting where necessary by asking follow-up questions. The focus of this part of the research is around the CoC, so the questions focused on this period.

Once satisfied with the result of the two pilot interviews and the data collected during them, it was possible to progress and attempt to interview the remaining candidates. All participants agreed to the use of a cassette tape-recorder.

IDENTIFYING, EXTRACTING AND CLASSIFYING RISKS

To facilitate the analysis of the risks identified from both the company records and the interviews together, it was necessary to create a structured risk taxonomy for the risks identified. This was developed by starting with the root risk 'The merger fails' and working "back" from there. If a risk did not contribute to the primary risk, then it was outside the scope of the research. By "working back" from there, a six-tier hierarchy was developed, into which each risk could be classified. This is illustrated below:

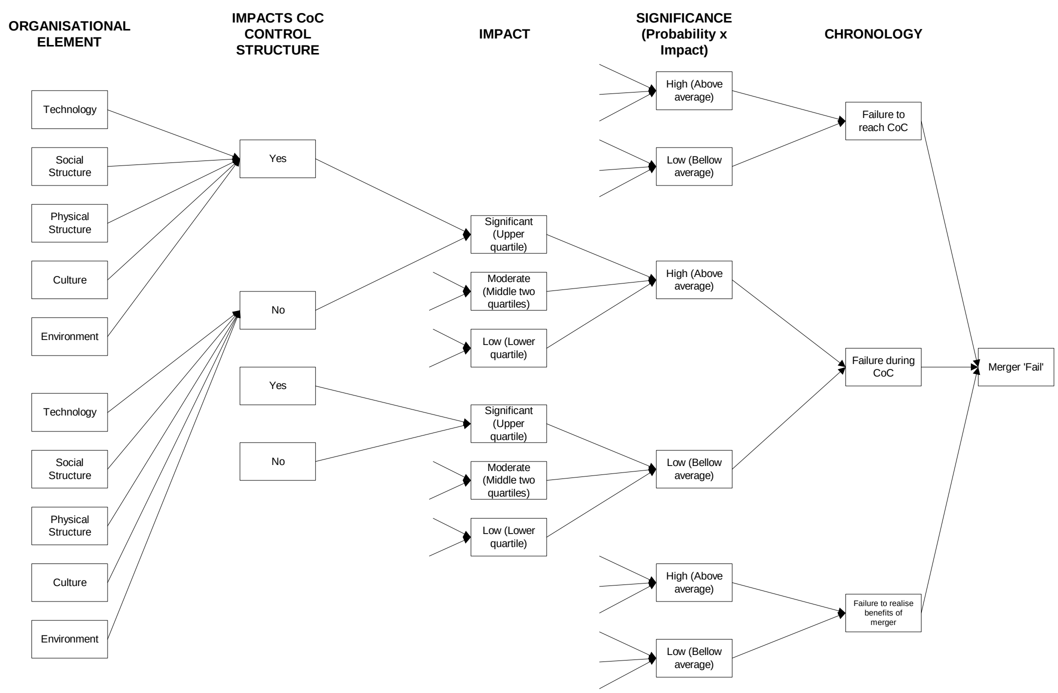

Figure 2 - Risk classification

Layer	***Contains***	***Valid Classifications***
Merger failure	Risks that could result in the merger failing	Yes
Chronology	When the risk can <u>first</u> occur	Pre-CoC CoC Post-CoC
Significance	What is the significance of the risk? For interview data this is based on the impact	High Low

Layer	*Contains*	*Valid Classifications*
	multiplied by the probability. Above average is rated high, otherwise it is rated as low. For document originated risks this is rated as high.	
Preparation	The level of preparation. For interview-originated risks this is based on the quartile into which the mitigation is rated as falling. For document-related risks this is rated as described earlier.	Significant Moderate Low
Impacts CoC structure	Can the risk impact the CoC control structure in any way?	Yes No
Organisational element	To which organisational element does the risk belong?	Technological Physical Cultural Social structure Environment
Specific risks	The specific risks which must fit into the structure.	

Table 2 - Risk classification

From a methodological perspective the risk classification is very useful. However, it needed to be useful from a practical standpoint also. The data gathered was made available as a database, which allows the risks to be treated as an n-dimensional cube which is "sliced and diced" in various ways, this I call the "risk cube". This means that a user of this database could select, for example, those external risks which could impact the CoC. This is useful because it allows management to allocate risks to the people who are going to manage the risks, and also as part of a systematic means to address risks in a grouped manner.

The risks are entered into a database as they are identified. Each risk is tagged with as much meta-data as possible. For each risk the following meta-data could be entered:

Metadata	*Description*
Risk number	A unique number assigned to each risk
Short name	Brief description of the risk
Description	More elaborate description of the risk
Merger	Can the risk impact the merger – Yes/No
CoC impact	Can the risk impact CoC – Yes exclusively/Yes inclusively/No
CoC manifestation	Can the risk manifest itself during CoC - Yes exclusively/Yes inclusively/No
Immediate impact	Does the risk have immediate impact – Yes/No
Impacts control centre	Can the risk impact the control centre or control centre structure - Yes exclusively/Yes inclusively/No
Average probability	Average probability of the risk occurring (only applies to the risks identified in the Delphi process, it is calculated at the end of each iteration) – score between 0 and 6
Average impact	Average impact of the risk occurring (only applies to the risks identified in the Delphi process, it is calculated at the end of each iteration) – score between 0 and 6
Average mitigation	Average level of mitigation of the risk occurring (only applies to the risks identified in the Delphi process, it is calculated at the end of each iteration) – score between 0 and 6
Source interview	The source of the risk is an interview – Yes/No
Source documents	The source of the risk is a reviewed document– Yes/No
Source literature	The source of the risk is public literature – Yes/No
Source	A reference to the source of the risk
Contributes to	Number of the risks that this risk contributes to
Pre-CoC	This risk can manifest itself during the pre-CoC phase
CoC	This risk can manifest itself during the CoC phase
Post-CoC	This risk can manifest itself during the post-CoC phase
Significance rating	The rating of the significance of the risk – High /Low

Metadata	*Description*
Mitigation rating	The rating of the mitigation of the risk – High /Moderate / Low
Organisational element rating	Coding of the organisational elemental category the risk belongs to – Technical/Social Structure/Culture/ Physical/Environment

Table 3 - Meta-data added to risk data

Transcribing every interview was the original intent. After the first three interviews transcription was showing little benefit. Instead, each interview was carefully listened to, and from it, a series of risks to the successful completion of the merger was identified. These were entered into a work document with a page for each interview. To guide this activity a comment would only be considered a risk if it , no matter how small, could impact or delay the completion of the change of control or the merger itself.

From each of these sheets the core risk was identified, for example a risk that might suggest that there is a danger that staff cannot use a particular tool is in essence the fact that staff are not familiar with, or trained to use, the tools available to them. By following this distillation process, and by combining risks from various interviews, a list of 55 risks was created. Each risk was assigned a unique reference number (Risk Number). The data relating to the classification of the risk was also entered with it. These included the phase of the merger the risk could impact.

THE QUESTIONNAIRE

Within the risk cube database is a special report which is used to produce the risk questionnaire. This questionnaire, plus a two-page instruction sheet, is sent to each participant. Participants evaluate each of the risks in terms of:

- Severity of the impact if it were to occur
- Probability of it occurring; and
- Degree to which the organisation was prepared to address the risk, i.e. the degree of mitigation.

Participants indicated any identified risks which they felt were not actually a valid risk. They were also instructed that if they felt they could not comment on a risk, they should just leave it blank. These results were also entered into the risk database.

Following initial analysis a second questionnaire was prepared for Delphi 2. This was similar to the first but also included the average value for each parameter (probability, impact and mitigation) from the first round (Delphi 1). This was sent to each participant. In addition, each participant was given a copy of the values they had chosen in Delphi 1. They then returned the questionnaire with their replies. This data was then entered into the database with the earlier data. The data from the two Delphi iterations was analysed.

In addition to examining the difference between iterations it is possible to test for changes in individual responses between iterations. To test if their replies had changed significantly between iterations the non-parametric Wilcoxon test is used. The analysis of the results from Delphi 1 and Delphi 2 indicated a third iteration was not required. In this example it could be concluded no further iterations were required.

Finally, a small number of outlier risks, (see the results section), were investigated to validate if this is a true reflection of the risk situation. It is reassuring if the investigation of this small set of risks indicates that the ratings are correct and justified. If they indicate that the risks correctly evaluated by the group, that indicates a very significant organisational issue as the groups understanding of the risk situation is at odds with what can be found with close inspection. This indicates that the organisation's perception of risk is not accurate and this is clearly a major concern
.

ANALYSIS & REPORTING

Having completed the Delphi study, it remains to analyse the data and present it. This section describes the primary analysis conducted and how the results were presented and communicated to management.

ANALYSIS

Imagine a well run, efficient organisation. If you were to map all of the risks it faced in terms of how significant they are (probability and impact) and how well prepared they were to address them, you would probably expect to see them map on a scatter diagram as a diagonal. The reason being the most significant risks over time would receive management attention to ensure the organisation was able to deal with them. Obviously since this is based on group opinion it is unlikely to be a perfect diagonal line, rather a general cluster. Risks which follow this type of pattern can be referred to as those which are effectively managed.

On the other hand risks which are so very well mitigated, compared to their relative significance, would suggest that these risks are being managed excessively. The opposite of that, where risks that are highly significant are not being well mitigated and those that are less significant are being very well mitigated, would be classified as negligently managed. These three broad situations are shown below in Figure 3 - Classification model of level of mitigation and significance of risks.

Of course, this is just a guideline. Where the boundary falls between these three "regions" on a scatter graph depends on all sorts of factors, including the organisations appetite to suppress risk. This will be influenced by various factors such as the organisational structure, market structure and the regulatory environment.

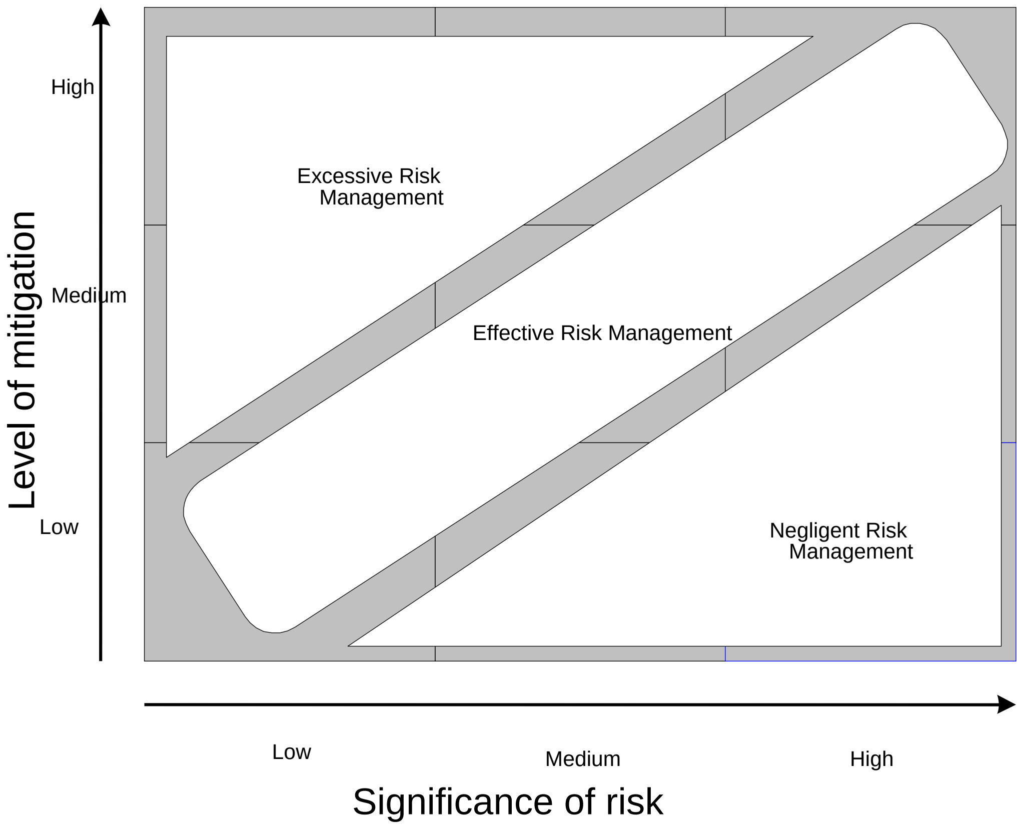

Figure 3 - Classification model of level of mitigation and significance of risks

To assist management understand their risk/mitigation relationship each risk is mapped onto a "scatter diagram" to indicate where possible areas of particular concern lie. An actual example of this is shown in Figure 4 - Significance

V mitigation scores, which follows.

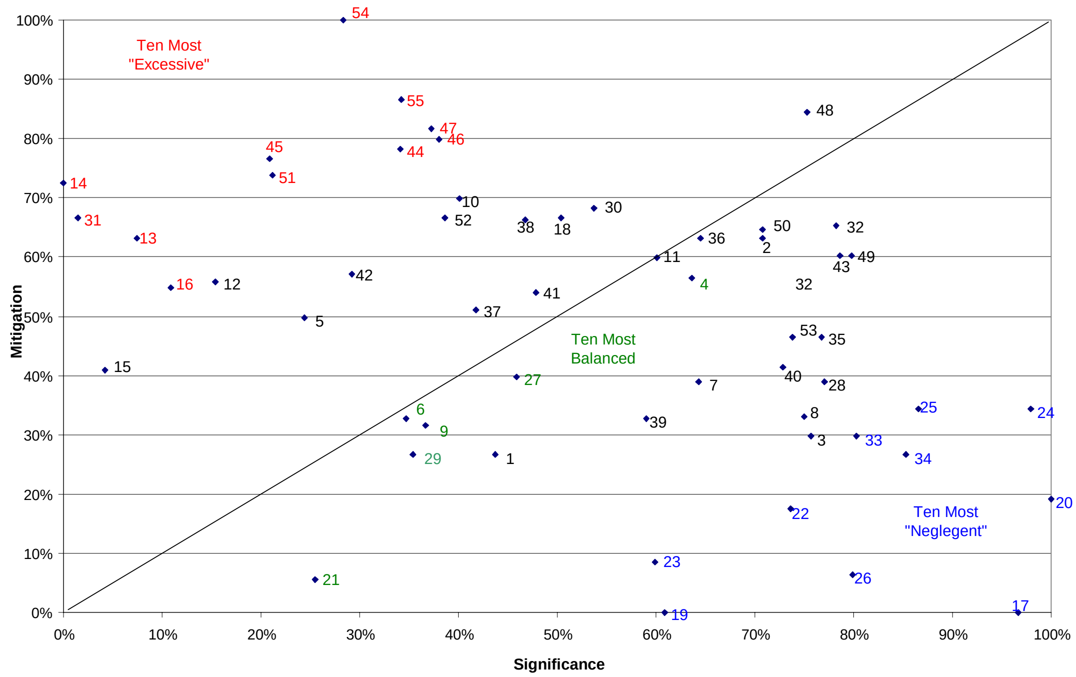

Figure 4 - Significance V mitigation scores

In this example, the diagonal line that well balanced effective risks management would follow is shown. The most balanced risks are indicated in green. These are risks which the organisation is basically managing appropriately. The most excessive risks are shown in red. In this situation the organisation has put more effort into managing these risks, or as was in this case, these are risks the organisation faces in its normal operating environment, and so, it has them well controlled and need take few extra steps to manage. Finally, the most negligent risks are shown in blue. These are risk which the organisation needs to focus its risk management efforts. These are both significant and the organisation is not well positioned to deal with them.

Examination of these specific risks indicated that these were risks that were raised by the merger and acquisition activity. These were outside of the normal operational domain for the organisation and so needed special action to be taken to mitigate or eliminate the risk.

The same data was also presented by sorting the risks by their significance and then showing the corresponding level of mitigation.

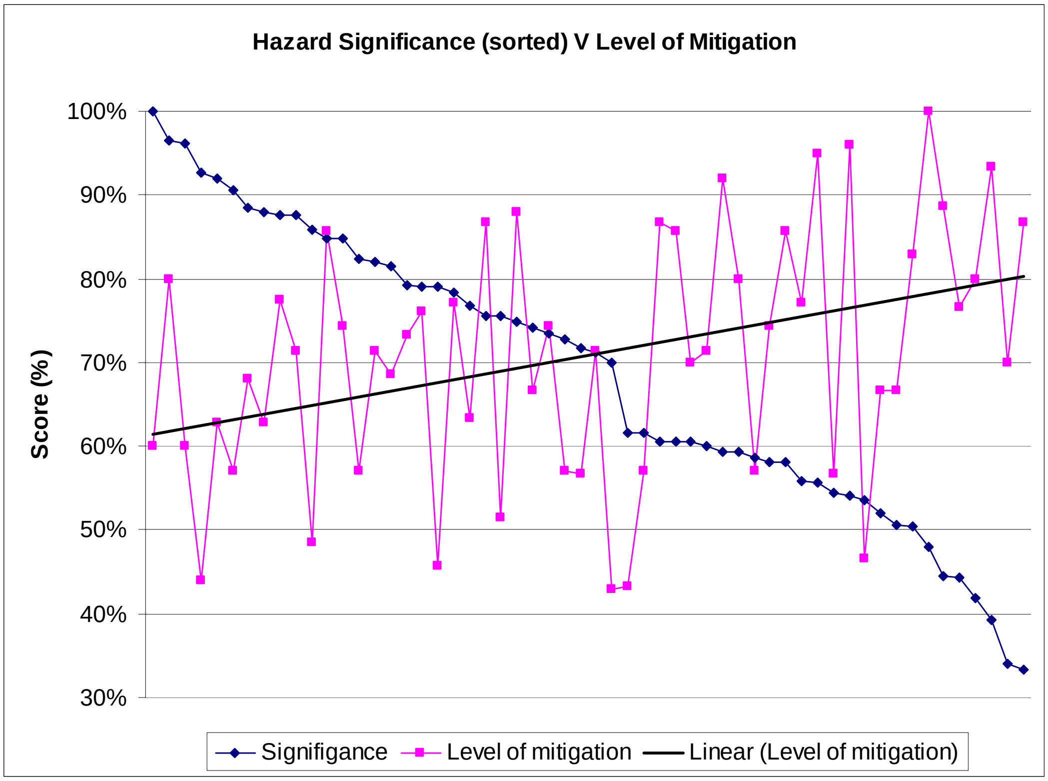

Figure 5 - Risk significance (sorted) versus level of mitigation

This way of illustrating the results illustrated the inverse relationship between the level of mitigation and the significance of the risks.

As indicated earlier the risks were also classified. This allowed risks to be analysed by one or more of the categories in the classification structure. The classification structure is coded consistently for all risks. This means that each risk isn't just placed in a hierarchy, but into any of the dimensions.

One example is shown in the following table (Table 4 - Classification of risks identified through the Delphi process), which indicated how each of the risks relates to the organisational area from which it originates. This showed that the majority of the risks the organisation faced were technological in nature, with social and cultural factors accounting for 16% and 13% respectively.

Organisational Area	**Number of risks**	**(%)**
External	0	0%
Physical	3	5%

Organisational Area	**Number of risks**	**(%)**
Social structure	7	13%
Culture	9	16%
Technology	36	65%

Table 4 - Classification of risks identified through the Delphi process

CONCLUSION

This paper is about methodology. The purpose is to describe a research method based on the Delphi method which can be used by practitioners and researchers alike to identify and build consensus relating to risk significance and current level of mitigation. The paper shows how it can be applied and reported upon. The method has proven valuable as it can be applied:

- Pre-facto and post-facto
- In many situations
- It avoids many of the usual issues with group interaction
- It builds consensus
- The reporting is easy to understand
- It can be applied quickly
- There is little impact on the target organization

BIBLIOGRAPHY OF AUTHOR

Michael McGrath is founder of Hibernia Consulting, a project delivery and risk management consulting firm serving major investment banking clients. He is a former regional CTO at Merrill Lynch and Project Delivery Director at both Bankers Trust and Deutsche Bank. He holds an MBA from the Smurfit School of Business and his Masters thesis won the Institute of Accountant's in Ireland gold medal for research in 1996. His doctoral research examined risk behaviour in unfamiliar problem domains by examining the risk behaviour of a major global bank.

He has published previously and presented at the British Academy of Management and presented internally at Cranfield colloquia.

APPENDIX 1 – RISK CLASSIFICATION

Risk Number	Classification
1	Culture
2	Technology
3	Culture
4	Culture
5	Social Structure
6	Technology
7	Technology
8	Social Structure
9	Technology
10	Technology
11	Technology
12	Technology
13	Physical
14	Physical
15	Physical
16	Social Structure
17	Technology

Risk Number	Classification
29	Technology
30	Technology
31	Technology
32	Technology
33	Culture
34	Social Structure
35	Technology
36	Technology
37	Technology
38	Technology
39	Technology
40	Technology
41	Technology
42	Technology
43	Technology
44	Technology
45	Technology

18	Technology
19	Social Structure
20	Social Structure
21	Culture
22	Culture
23	Culture
24	Technology
25	Culture
26	Technology
27	Technology
28	Technology

46	Technology
47	Technology
48	Technology
49	Social Structure
50	Culture
51	Technology
52	Technology
53	Technology
54	Technology
55	Technology

APPENDIX 2 – DELPHI 1 & 2 RESULTS

Average of standard deviations	**Probability**	**Impact**	**Mitigation**
Delphi 1	1.15	1.11	1.02
Delphi 2	1.12	1.10	1.00

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A GROUP COGNITIVE APPROACH TO OPERATIONAL RISK IDENTIFICATION AND EVALUATION

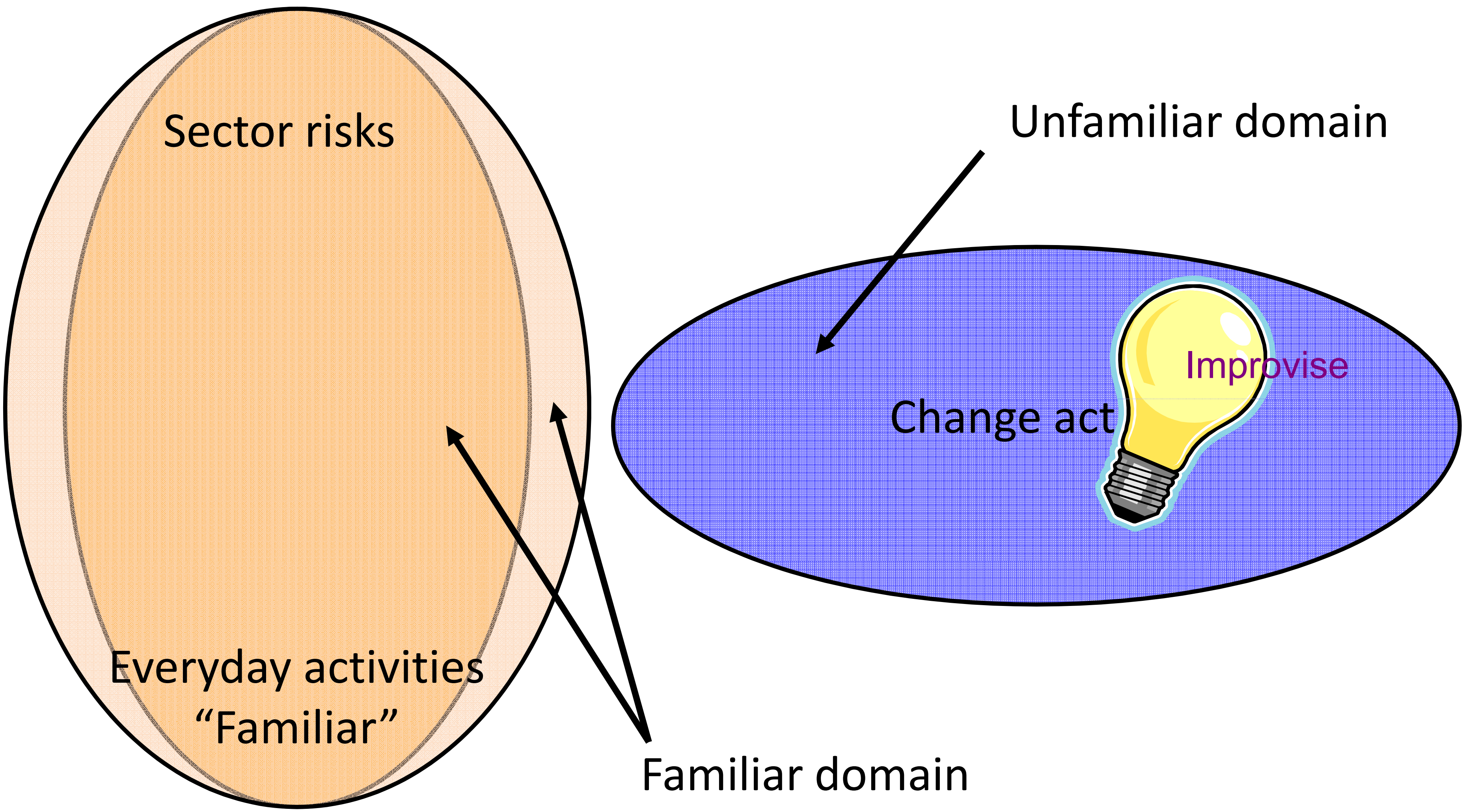
Cognitive Risk Identification and Measurement - CRIM

Dr. Michael McGrath

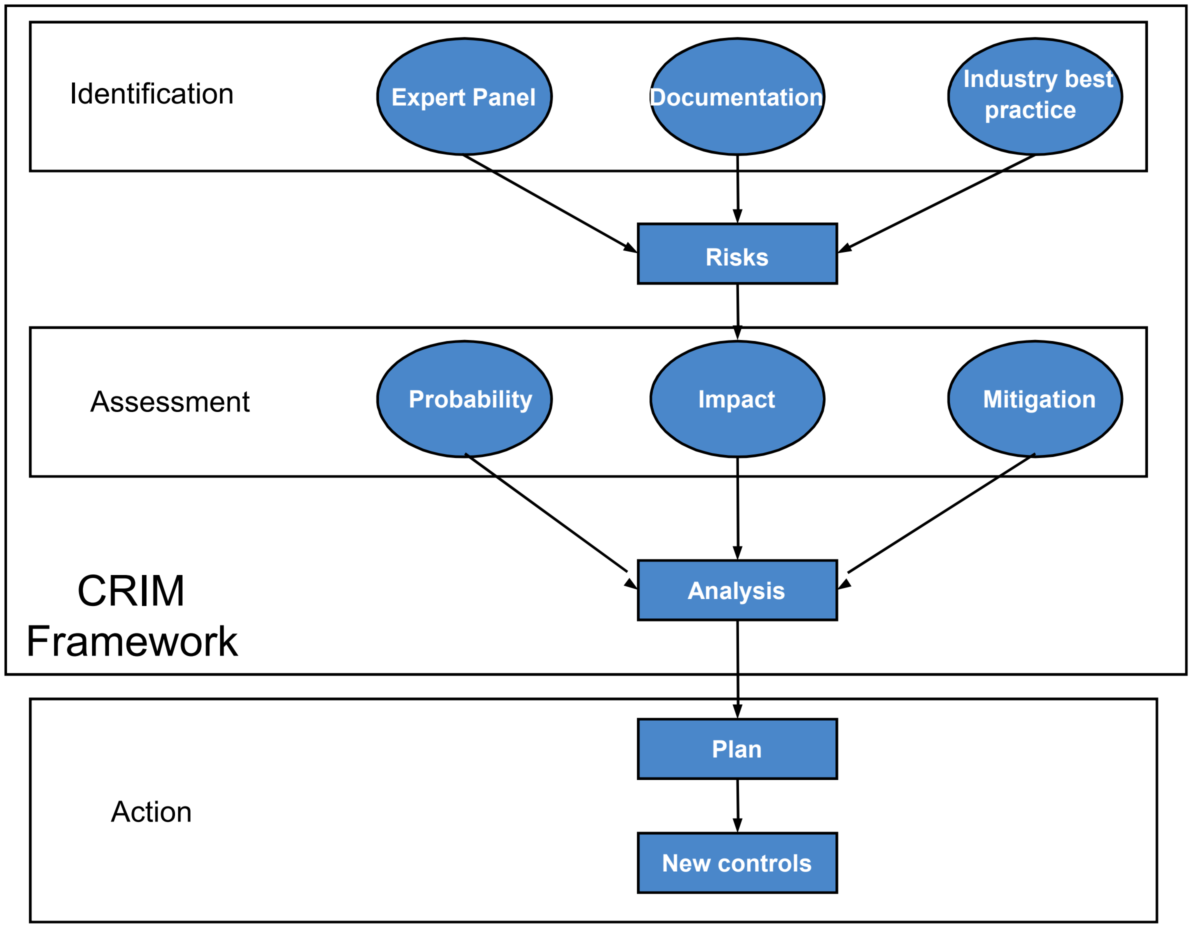
Objectives and background

- Academic research
  - Investment banking, proprietary M&A
  - Change of Control
- Low impact on target organisation
- Quick

Familiar and unfamiliar domains



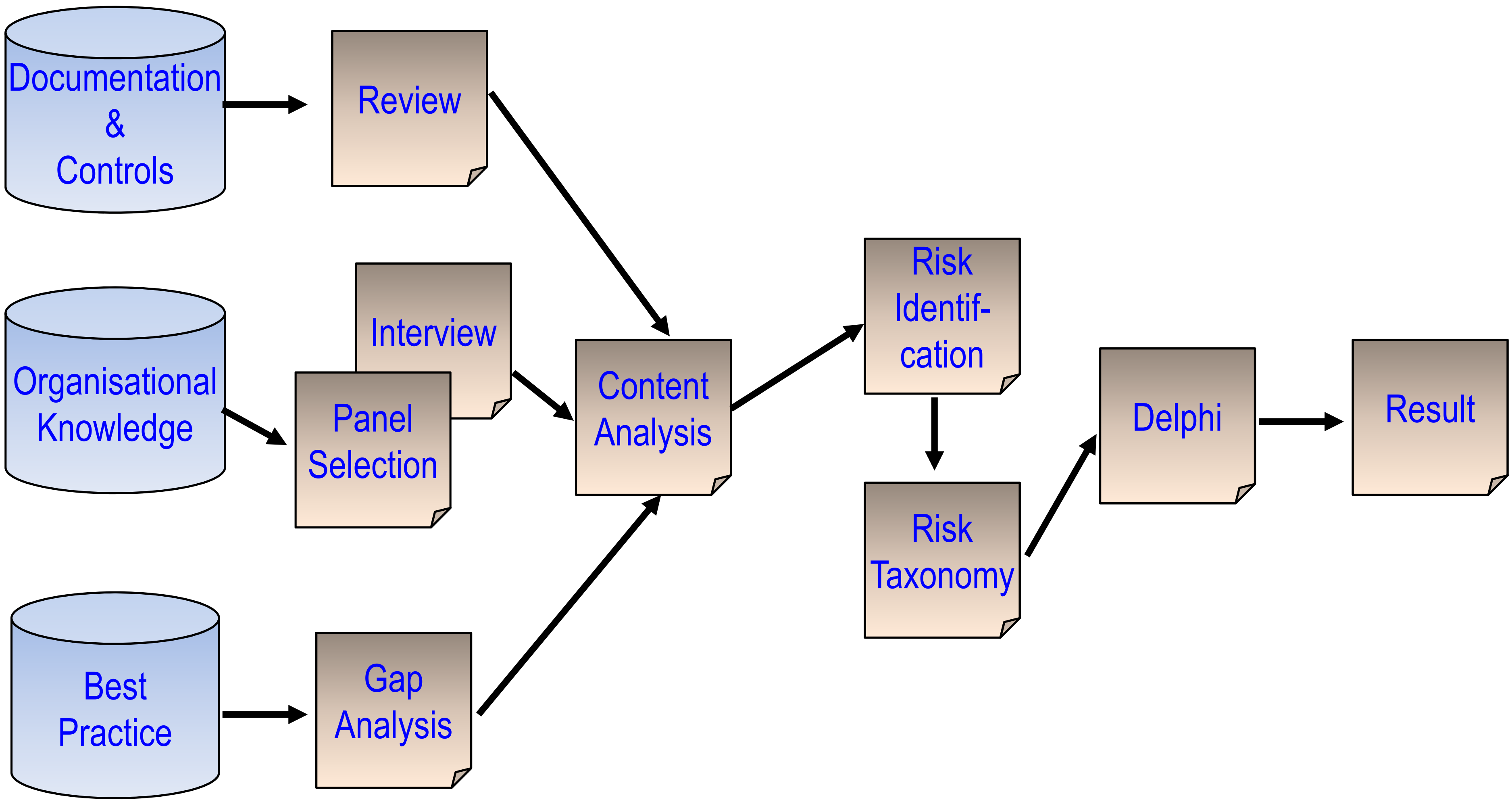
Fitting the existing risk framework



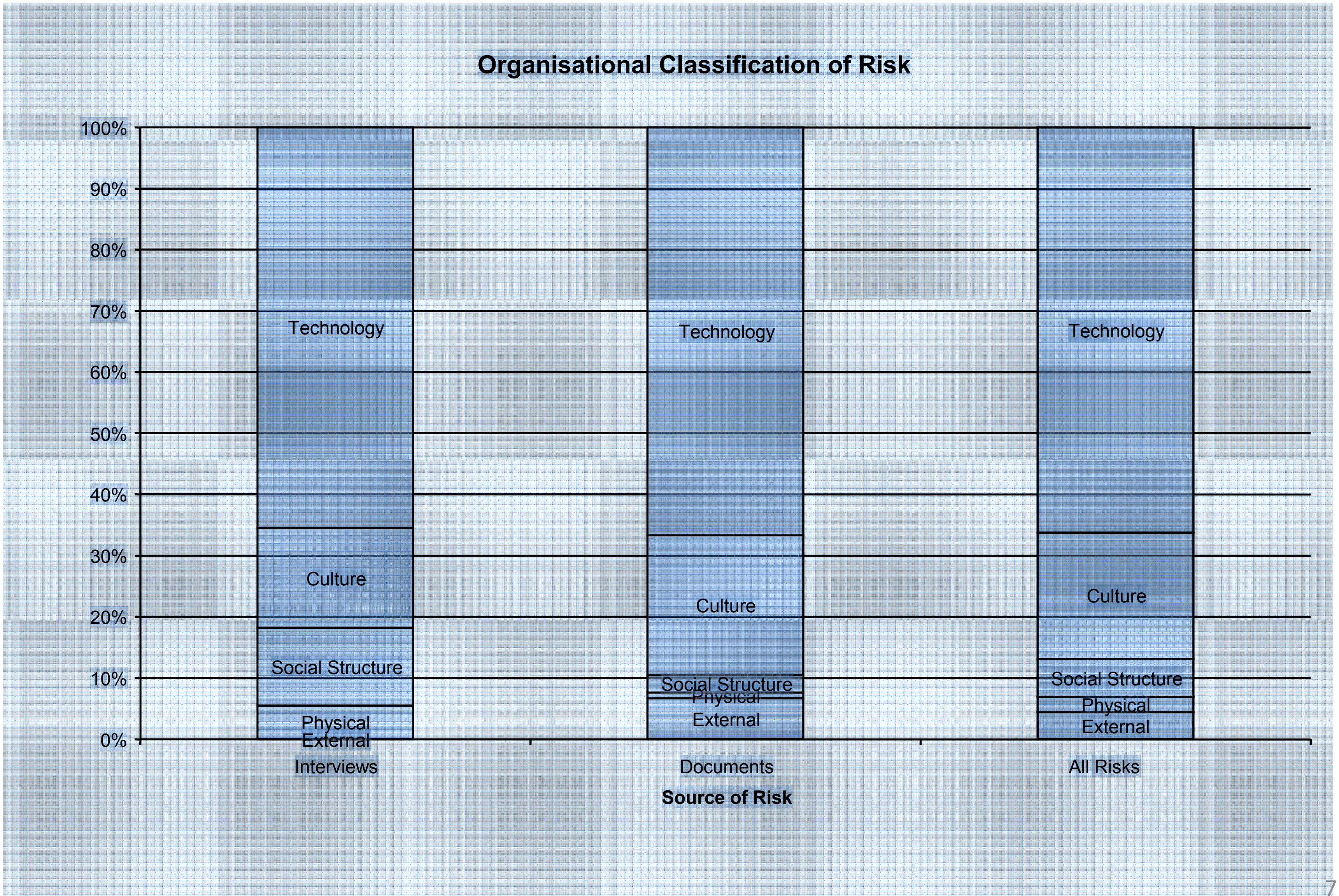
Options Considered

- Review the company records (from the first acquisition) and identify the documented risks
- Interview the panel of experts (internal & external)
- Organise a workshop or focus group session with the experts.

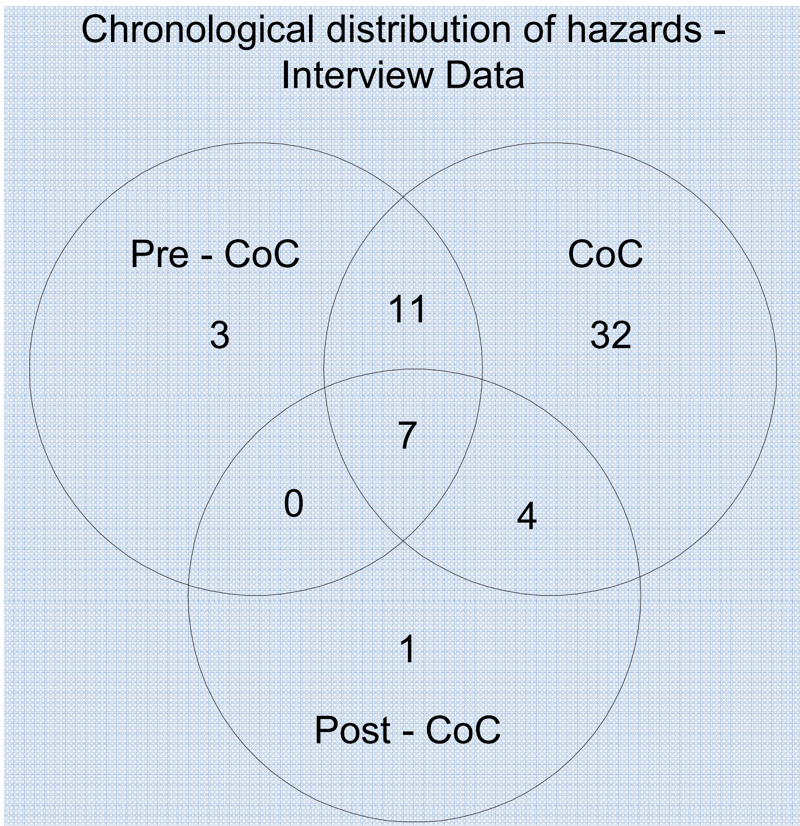
What to do? CRIM

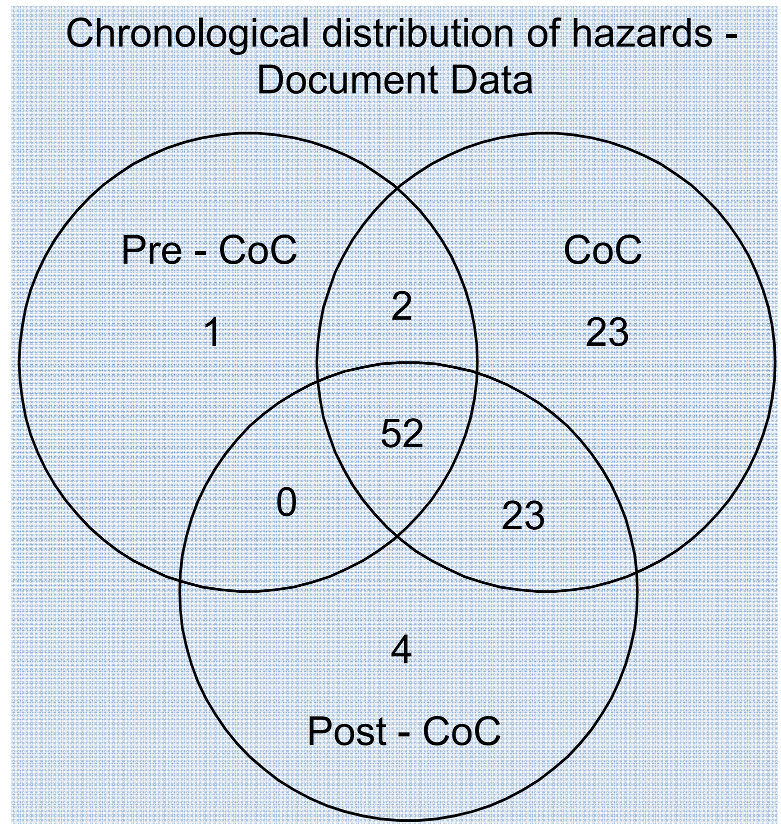


Formal V tacit focus

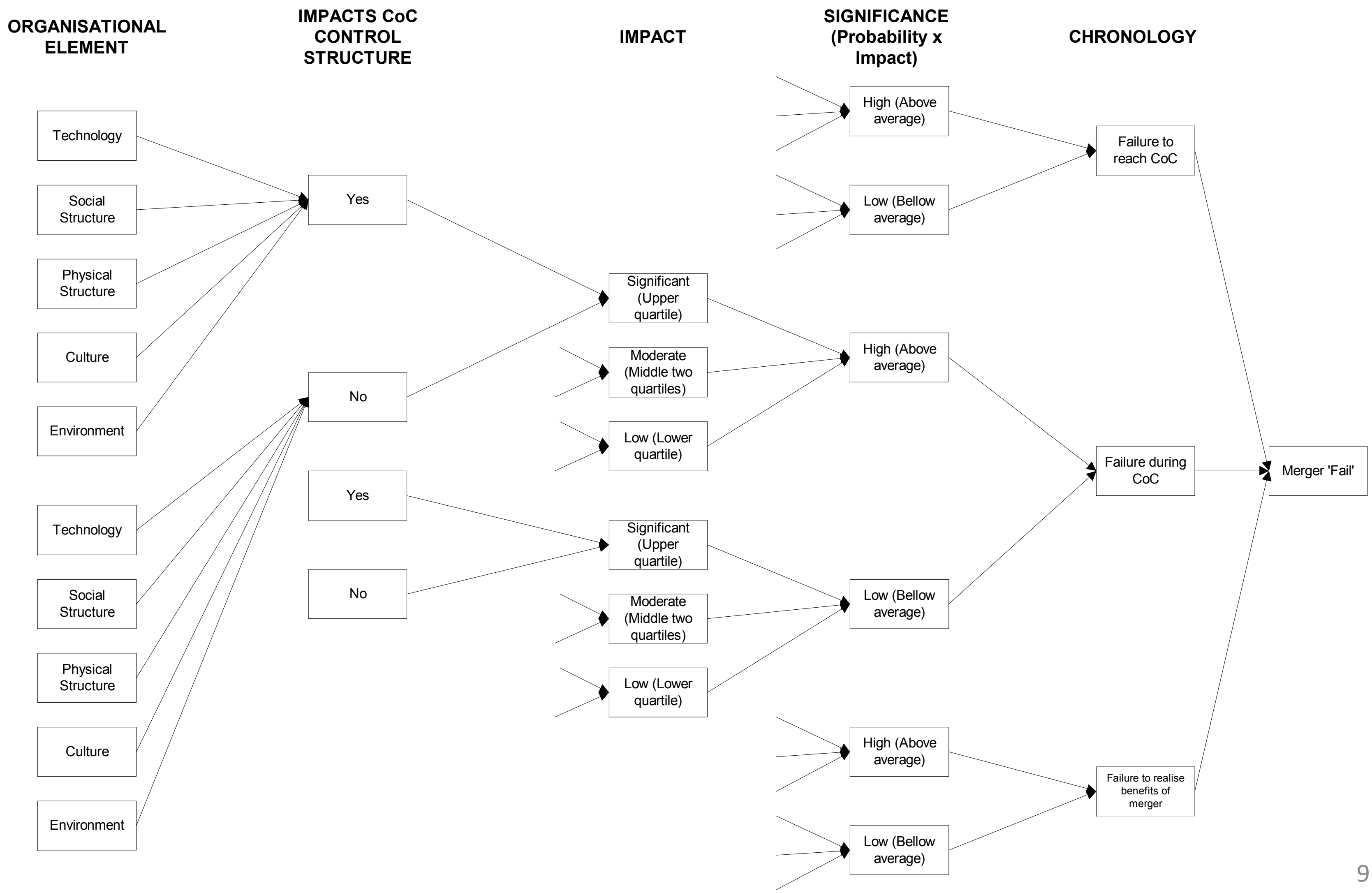


Formal V tacit focus

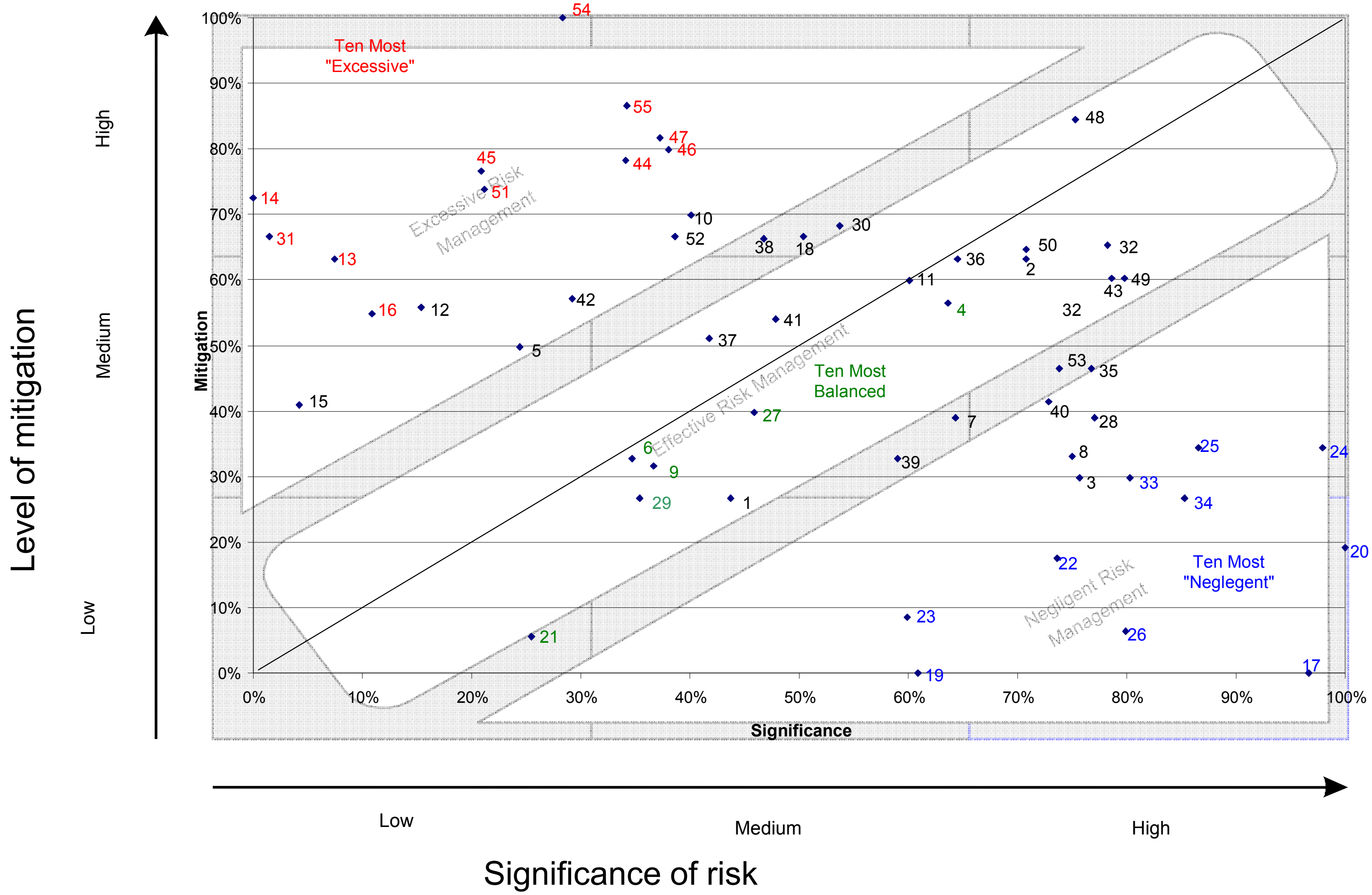




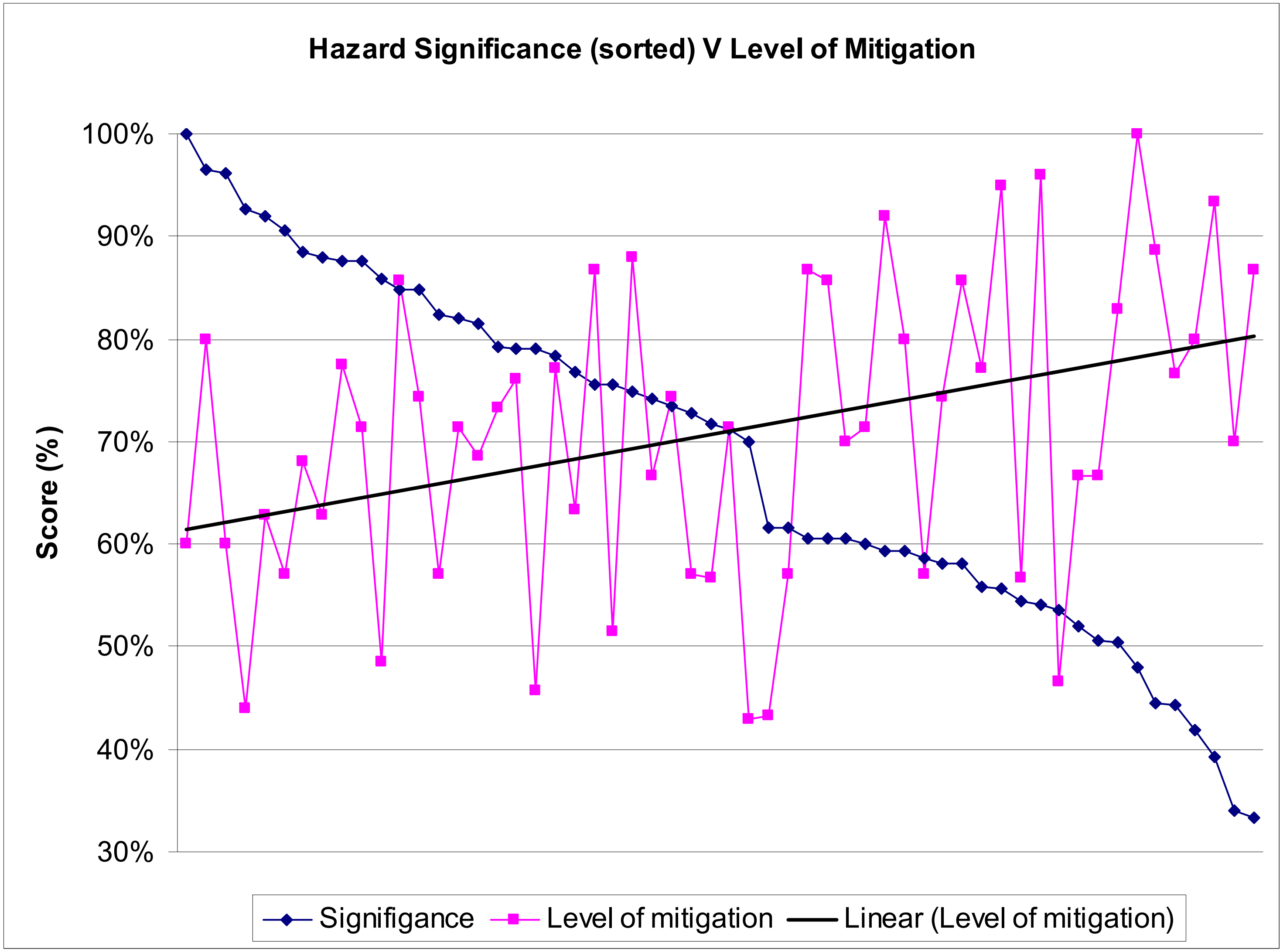
Risk Taxonomy



Results and Outliers



Results (cont.)



CRIM Overview

- Pre-facto and post-facto
- In many situations
- It avoids many of the usual issues with group interaction
- It builds consensus
- The reporting is easy to understand
- It can be applied quickly
- There is little impact on the target organization

Multivariate Models for Operational Risk

Klaus Böcker, HypoVereinsbank AG

2007 Enterprise Risk Management Symposium
A1 Scientific Papers No. 1
March 28-30, Chicago, IL, USA.

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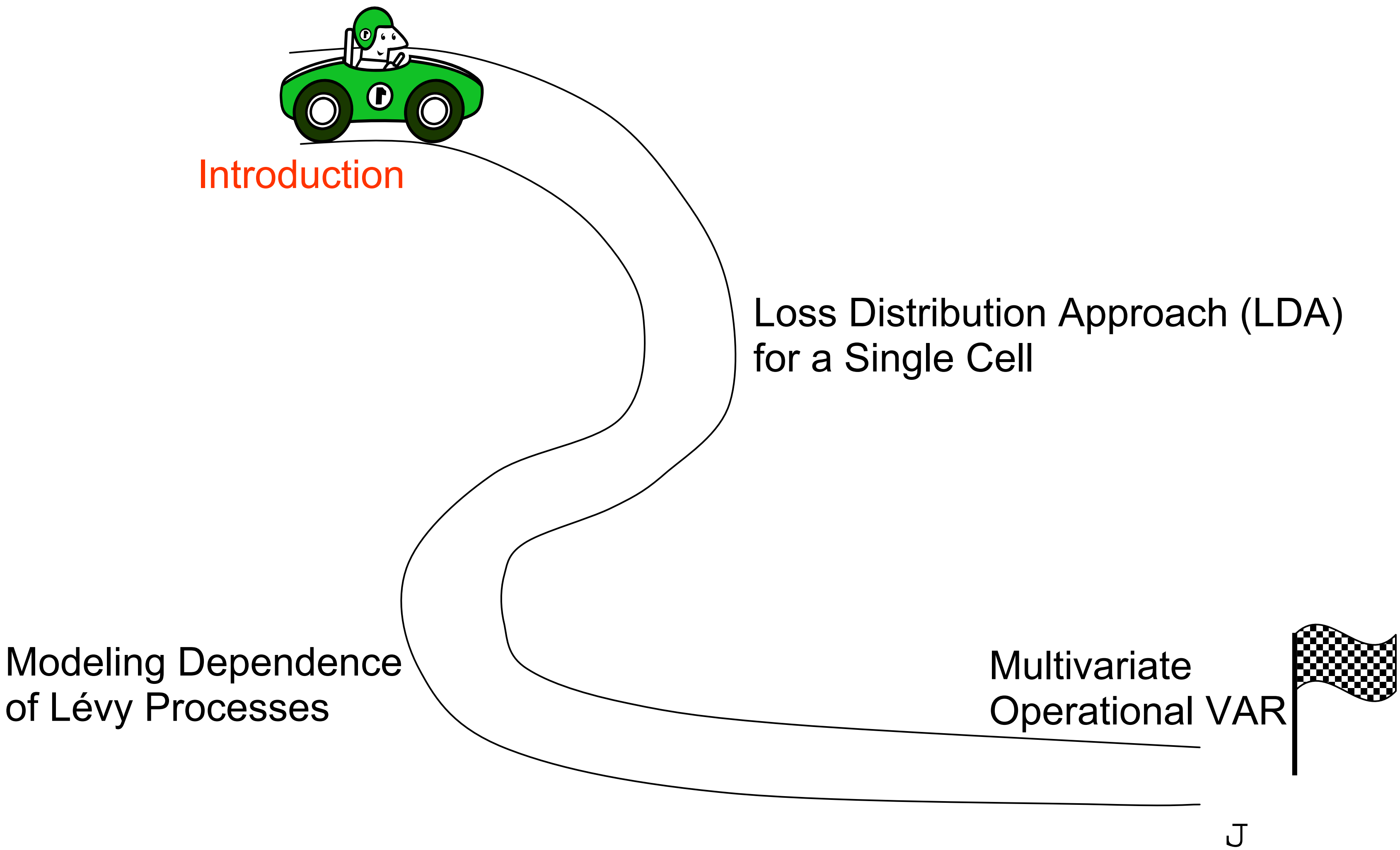
Disclaimer:

The opinions expressed in this talk are those of the speaker and do not reflect the views of HypoVereinsbank or UniCredit.

J

Outline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Introduction

- **Definition of Operational Risk:**

  The risk of losses resulting from inadequate or failed processes, people and systems, or external events (BASEL II).

- **Basel II:**
  - Basic Indicator Approach
  - Standardised Approach
  - Advanced Measurement Approaches (AMA)

- **Economic Capital**

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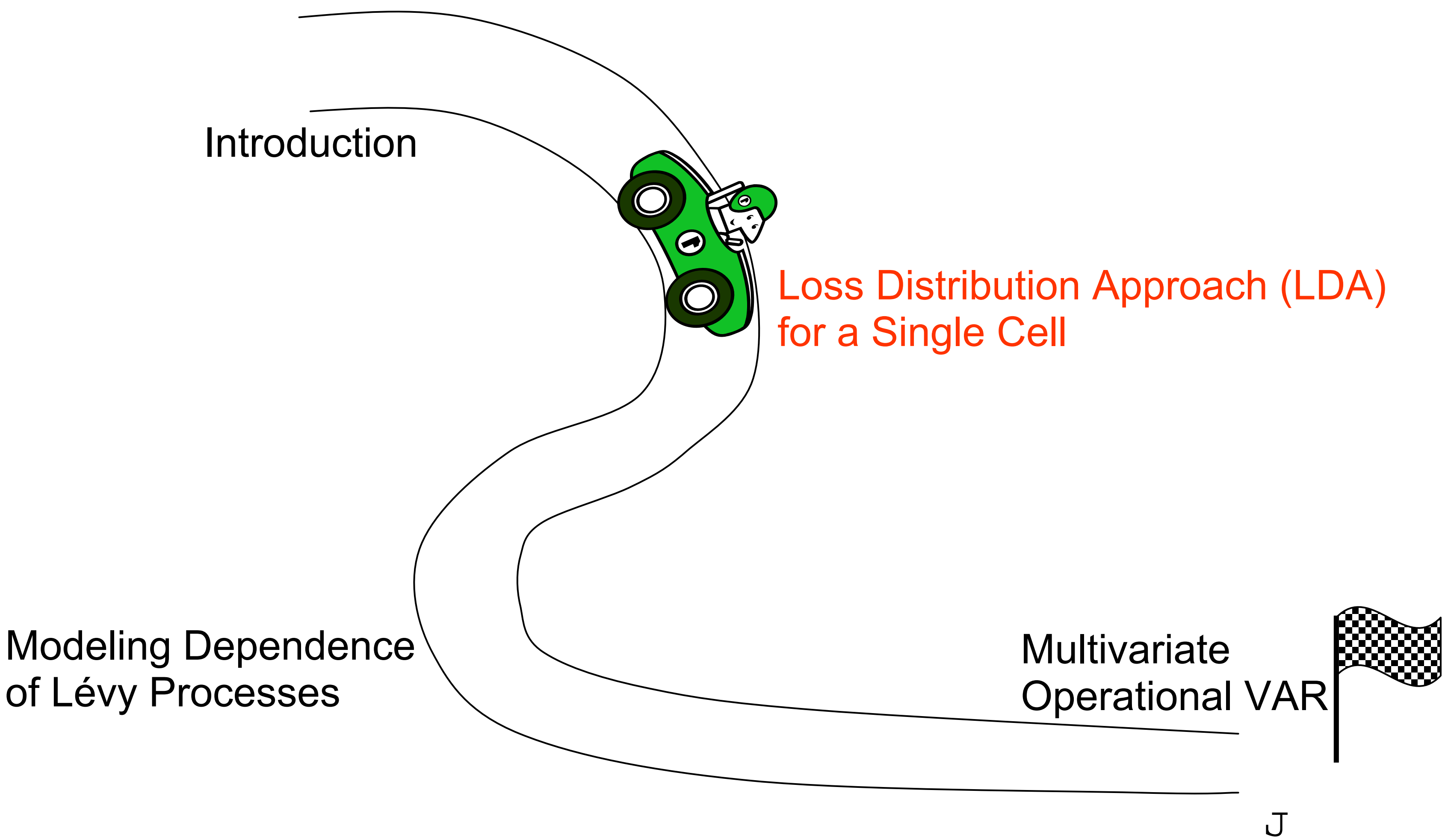
Outline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The Loss Distribution Approach

Standard LDA model:

- The loss severities $(X_k)_{k \in \mathbb{N}}$ are positive iid random variables describing the magnitude of each loss event.
- The number $N(t)$ of loss events in the time interval $[0,t],\ t \geq 0$ is random and is described by the frequency process $(N(t))_{t \geq 0}$.
- The severity process and the frequency process are assumed to be independent.
- The aggregate loss process is given by

$$S(t) = \sum_{k=1}^{N(t)} X_k, \qquad t \geq 0.$$

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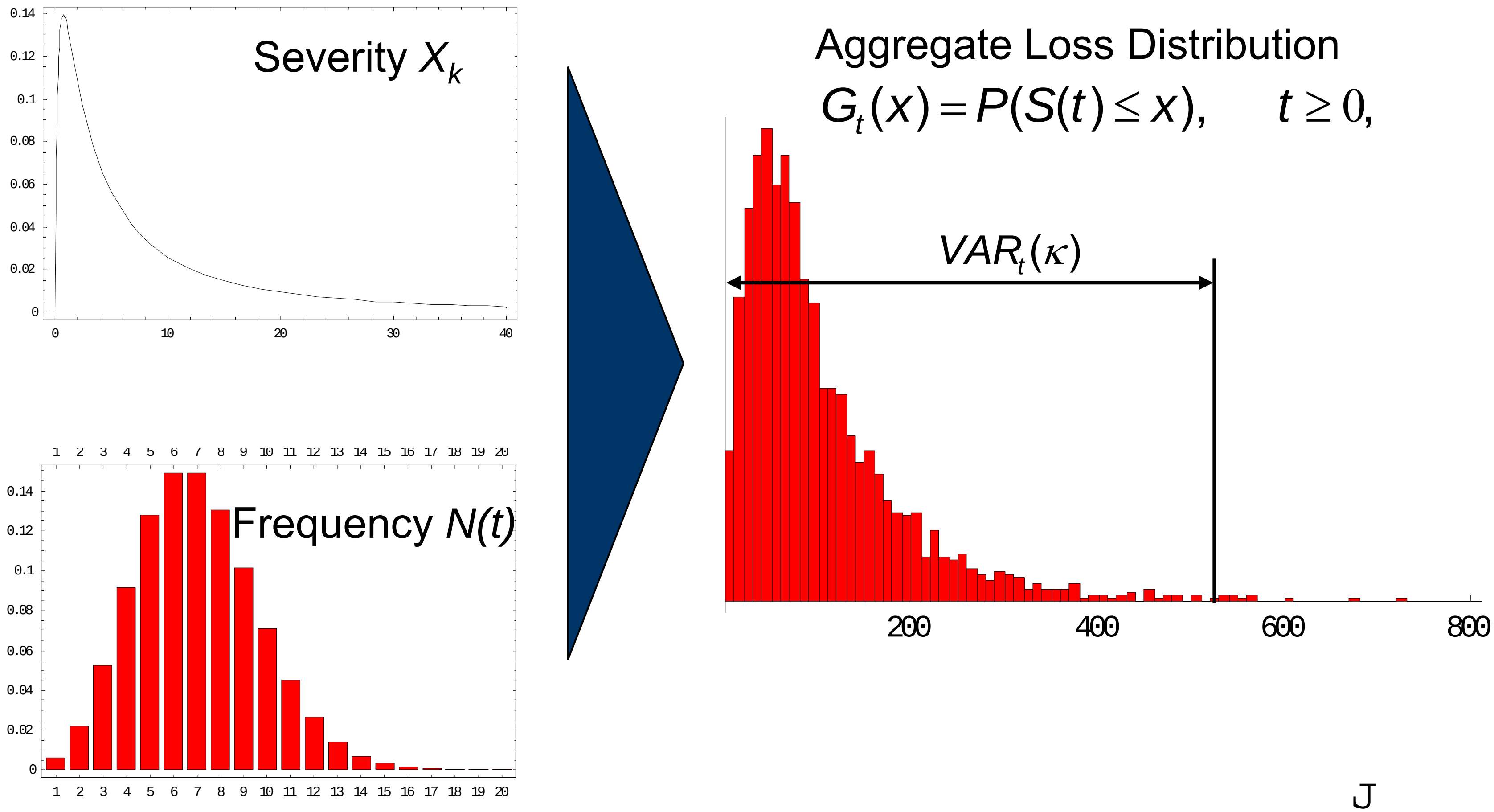
Aggregate Loss Distribution



Operational VAR

- Define the aggregate loss distribution function

$$G_t(x) = P(S(t) \le x), \qquad t \ge 0.$$

- Operational VAR (OpVAR) at confidence level κ is just a quantile of the aggregate loss distribution:

$$VAR_t(\kappa) = G_t^{\leftarrow}(\kappa) = \inf\{x \in R : G_t(x) \ge \kappa\}, \quad \kappa \in (0,1)$$

where $G_t^{\leftarrow}$ is the generalized inverse of G_t .

- In general, $VAR_t(\kappa)$ cannot be analytically calculated.

J

The Single-Loss Interpretation

Severity distributions are usually heavy-tailed.

Subexponentiality:

A random variable with distribution function *F* is subexponential if their iid sum is most likely to be very large because of one of the terms being very large:

$$\lim_{x\to\infty} \frac{P(X_1 + \cdots + X_n > x)}{P(\max(X_1, \ldots, X_n) > x)} = 1, \qquad \text{for some (all) } n \geq 2.$$

Single-loss interpretation of operational VAR:
OpVAR is due to one single big loss rather than due to an accumulation of small losses.

Theorem of the Analytical OpVAR

The single-loss interpretation simplifies OpVAR:

- In a Standard LDA model with fixed $t > 0$ (e.g. $t = 1$ year) and subexponential distribution severity F, we have that

$$VAR_t(\kappa) = F^{\leftarrow}\left(1 - \frac{1-\kappa}{EN(t)}\big(1 + o(1)\big)\right), \qquad \kappa \to 1,$$

  where $EN(t)$ is the expected frequency.

- Set $EN(t) = \lambda\, t$ for a Poisson distributed frequency.

J

Popular Severity Distributions...

Name	Distribution Function	Parameters
Lognormal	$F(x) = \Phi\left(\frac{\ln x - \mu}{\sigma}\right)$	$\mu \in R, \sigma > 0$
Weibull	$F(x) = 1 - e^{-(x/\theta)^{\tau}}$	$\theta > 0, 0 < \tau < 1$
Pareto	$F(x) = 1 - \left(1 + \frac{x}{\theta}\right)^{-\alpha}$	$\alpha, \theta > 0$

J

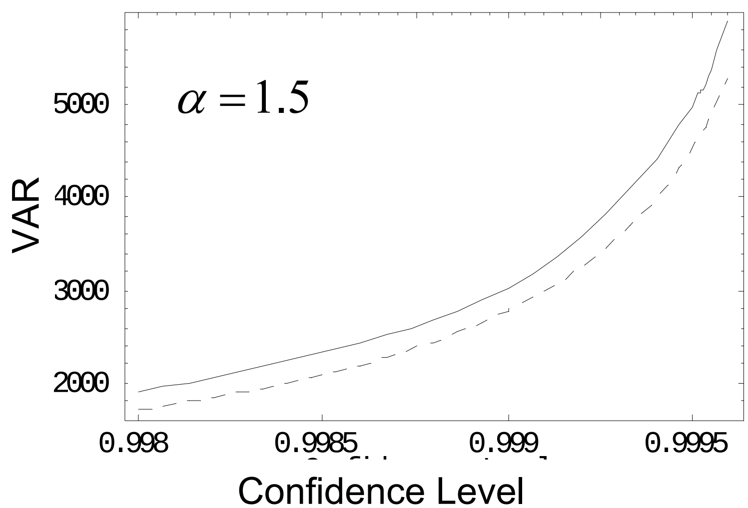
...And Their Approximated OpVARs

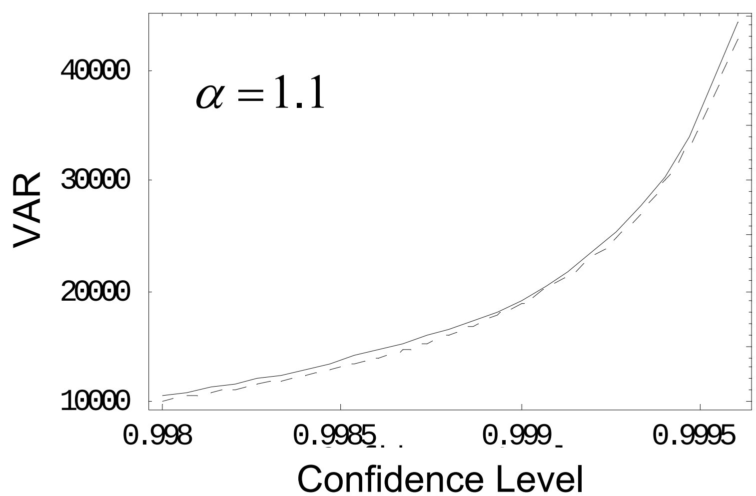
Name	$VAR_t(\kappa)$ as $\kappa \to 1$
Lognormal	$\exp\left[\mu - \sigma\,\Phi^{-1}\left(\frac{1-\kappa}{EN(t)}\right)\right]$
Weibull	$\theta\left[\ln\left(\frac{EN(t)}{1-\kappa}\right)\right]^{1/\tau}$
Pareto	$\theta\left[\left(\frac{EN(t)}{1-\kappa}\right)^{1/\alpha} - 1\right] \sim \theta\left(\frac{EN(t)}{1-\kappa}\right)^{1/\alpha}$

J

Illustration for Pareto Severities

Approximated OpVAR (dashed line) and simulated OpVAR (solid line) for the Pareto-Poisson LDA (with $\theta = 1$).





MC simulation ———————

OpVAR approximation - - - - - - - - -

J

Refinement of The Single Loss Approximation

- Single-loss interpretation: Only one single loss counts for OpVAR
- What about the other (n -1) losses in $S = \sum_{k=1}^{n} X_k$?

➡ Assume that severities have finite expectation $\mu = EX_k$.

Empirical analysis suggests a refined OpVAR approximation:

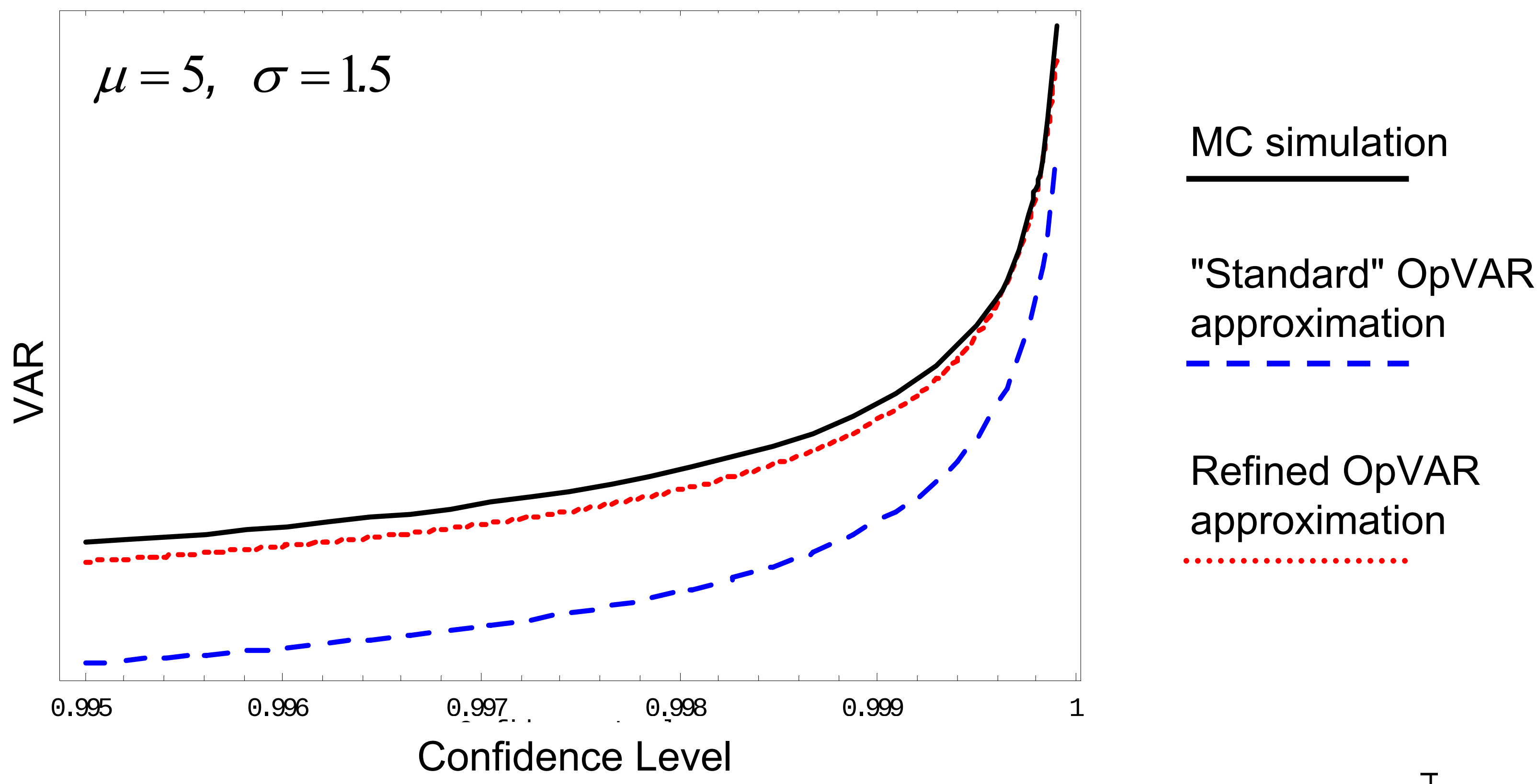
$$VAR_t(\kappa) = F^{\leftarrow}\left(1 - \frac{1-\kappa}{EN(t)}\left(1 + o(1)\right)\right) + \left(EN(t) - 1\right)\mu, \quad \kappa \to 1.$$

mean correction of (n-1) single losses

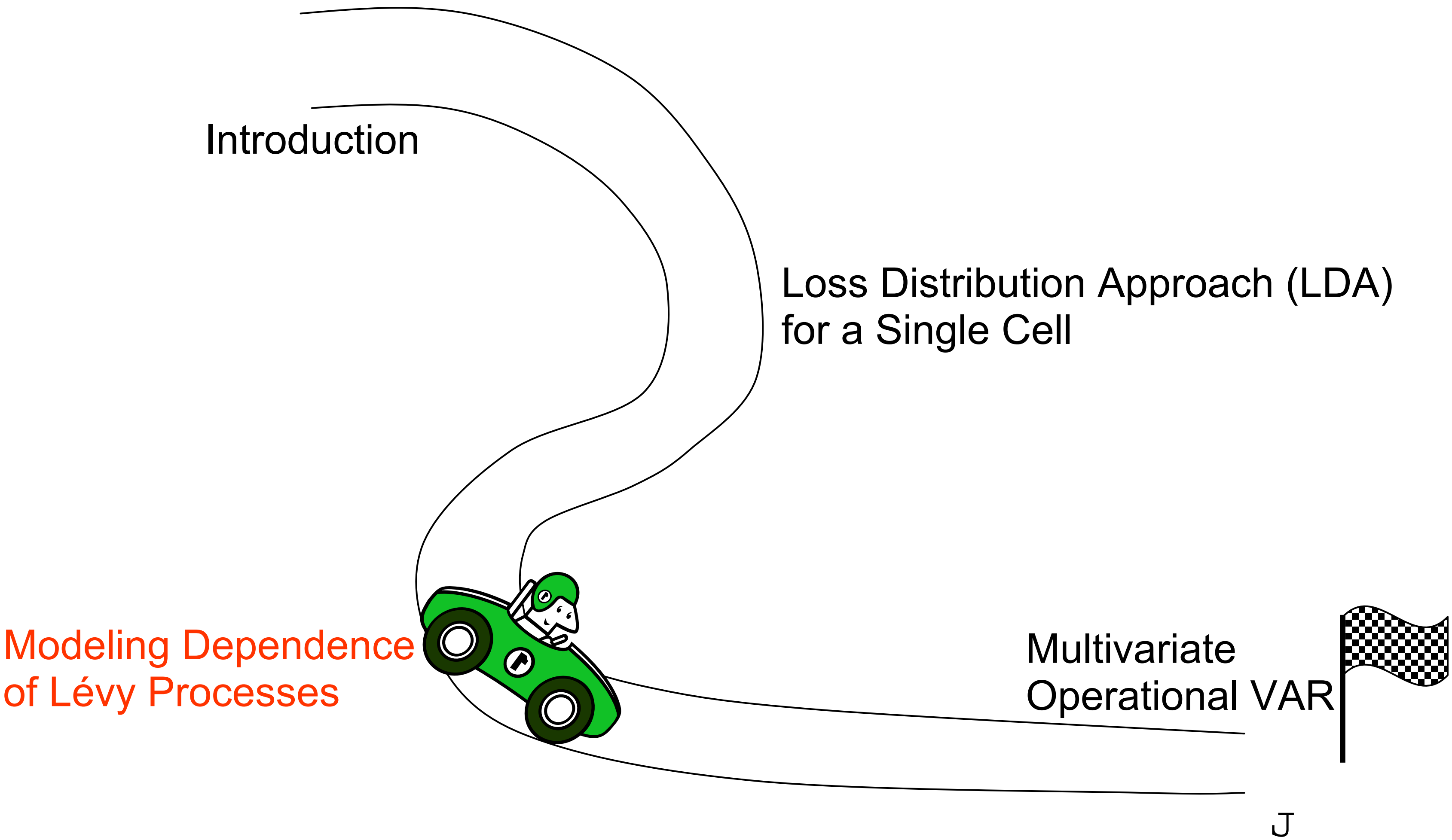
J

Refinement of The Single Loss Approximation

Illustration for lognormal distributed severities.



Outline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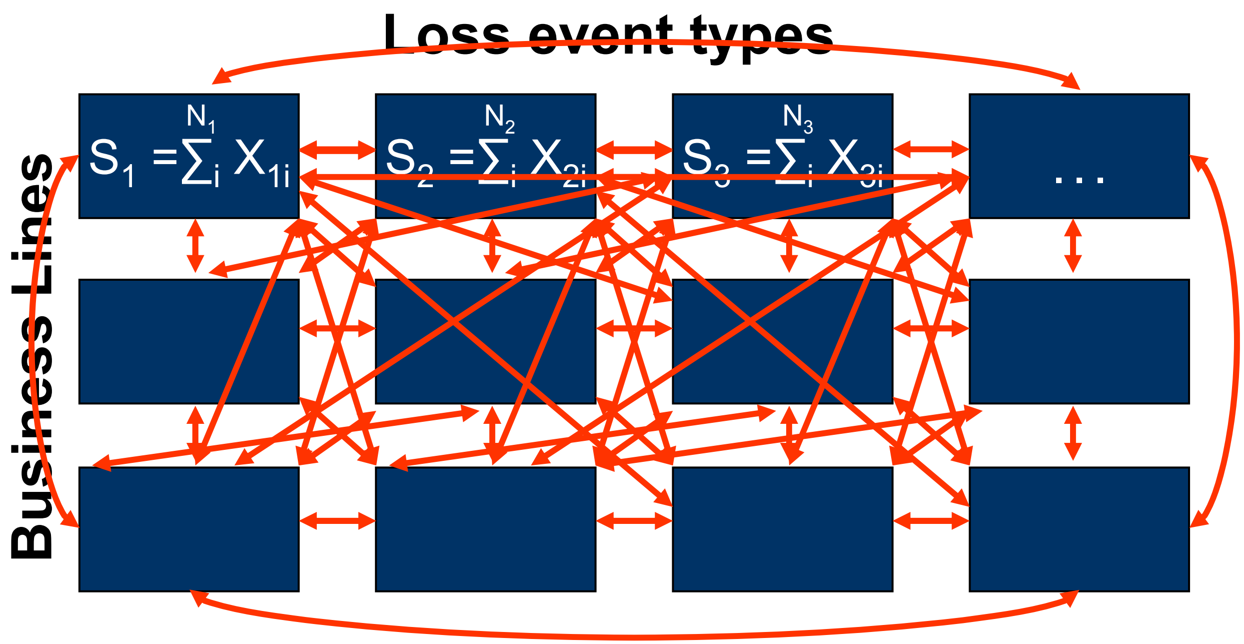
The Multivariate OpRisk Problem

Introduce operational-risk cells and their dependence:



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Lévy Processes in Operational Risk

Properties of *S*(*t*):

- Severities X_k are stationary over time.
- Severities X_k are independent.
- No operational "gain" occurs: $X_k \geq 0$

↓

- Aggregate Loss *S* can be modelled by a Lévy processes with only positive jumps (Spectrally positive Lévy processes).
- Lévy processes are determined by their <u>Lévy measure Π</u>.

J

Lévy Measures And Tail Integrals

- The Lévy measure $\Pi(dx)$ measures the
  - expected number of losses per unit time
  - with a loss amount in the range [x, $x + dx$].

- The tail integral $\overline{\Pi}$ gives the expected number of losses per unit time above $x \in [0,\infty)$, that is $\overline{\Pi}(x) = \Pi([x,\infty))$.

- **Example:** Homogenous compound Poisson process with intensity λ and severity distribution $F(x)$:

Lévy measure: $\Pi([0,x)) = \lambda\, P(X \leq x) = \lambda\, F(x)$

Tail integral: $\overline{\Pi}(x) = \lambda\, P(X > x) = \lambda\, \overline{F}(x) = \lambda\,(1 - F(x))$

J

Multivariate Processes And Lévy Copulas

- Recipe for building multivariate joint distributions (Sklar, 1959):

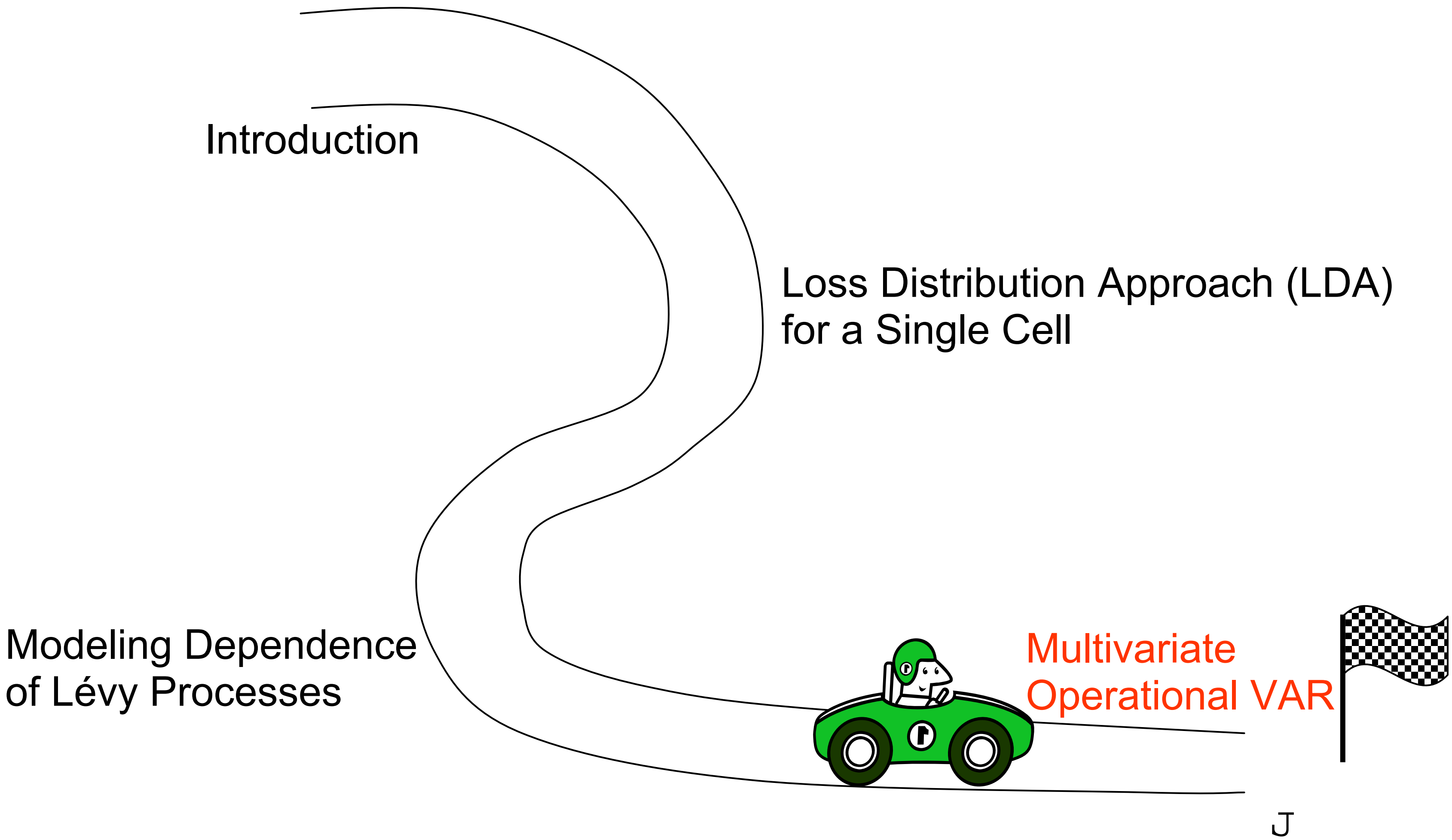
Marginal distributions $F_1(x_1), \ldots, F_n(x_n)$	+	Copula	=	Multivariate distribution $F(x_1, \ldots, x_n)$

- Similarly: Multivariate tail integrals can be constructed from marginal tail integrals by means of Lévy Copulas (Cont and Tankov, 2004):

Marginal tail integrals $\overline{\Pi}_1(x_1), \ldots, \overline{\Pi}_n(x_n)$	+	Lévy Copula	=	Multivariate tail integral $\overline{\Pi}(x_1, \ldots, x_n)$

J

Outline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The Univariate SCP Model

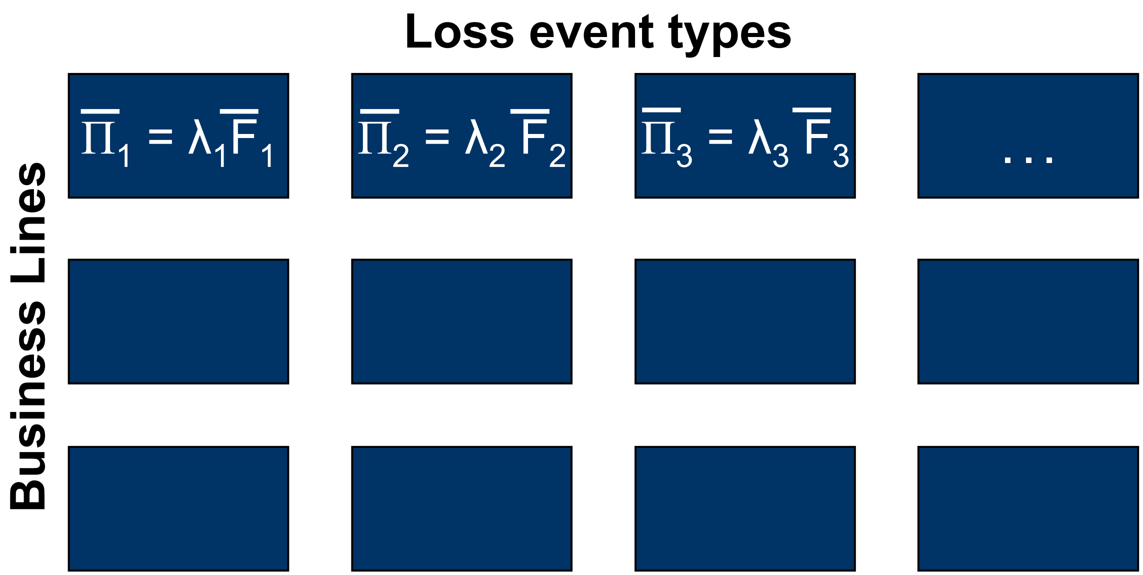
Definition: Subexponential compound Poisson (SCP) model:

- It is a Standard LDA model based on $S = \sum_{k=1}^{N(t)} X_k$.
- The X_k have subexponential severity distribution $F(x)$.
- $N(t)$ follows a homogenous Poisson process with intensity λ,
- The tail integral is given by $\overline{\Pi}(x) = \lambda \overline{F}(x) = \lambda (1 - F(x))$.

J

The Multivariate SCP Model

Each cell $i = 1,\ldots,d$ is described by an univariate SCP model with tail integral $\overline{\Pi}_i(\cdot) = \lambda_i \, \overline{F}_i(\cdot)$.



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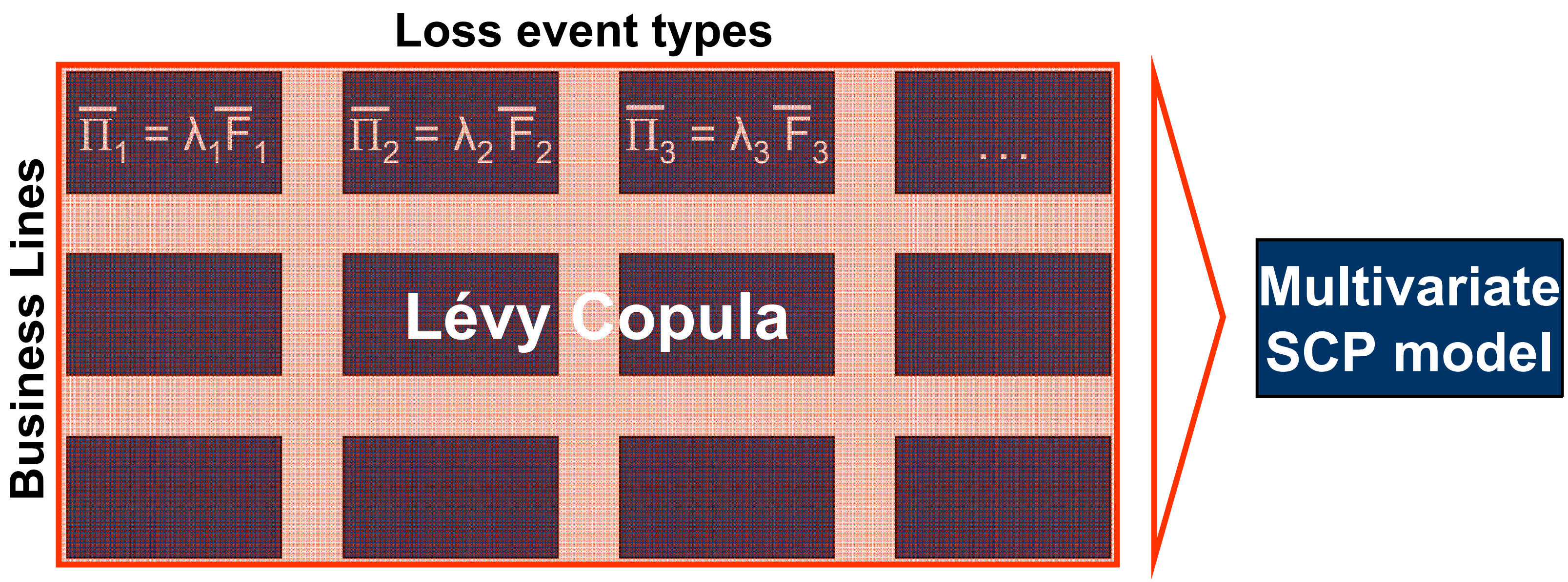
The Multivariate SCP Model

Each cell $i = 1,\ldots,d$ is described by an univariate SCP model with tail integral $\overline{\Pi}_i(\cdot) = \lambda_i \overline{F}_i(\cdot)$.



$$\hat{C}\left(\lambda_1 \overline{F}_1(x_1), \ldots, \lambda_d \overline{F}_d(x_d)\right) = \overline{\Pi}(x_1,\ldots,x_2) \quad \triangleright \quad S = (S_1,\ldots,S_d)$$

Total Aggregate Loss And Total OpVAR

- The bank's total aggregate loss process

$$S^{+}(t) = S_1(t) + S_2(t) + 6 \ + S_d(t), \qquad t \geq 0.$$

is compound Poisson with Parameters λ^{+} and F^{+}.

- For a given Lévy copula, λ^{+} and F^{+} can be calculated.

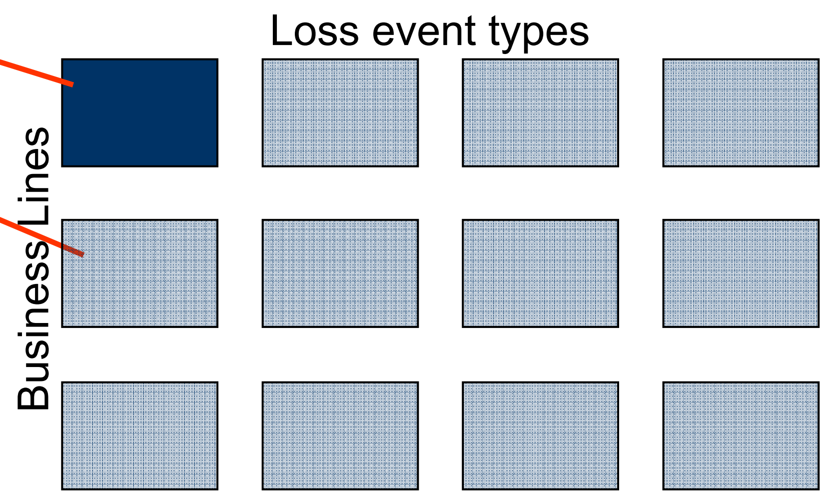
- Given λ^{+} and F^{+}, the analytical OpVAR theorem can be applied to obtain total OpVAR VAR_t^{+}.

Frequency correlation has (asymptotically) no impact on OpVAR.

J

Completely Dominating Cell VARs

- Tail dominating Pareto cell: $\overline{F}_i(x) = o(\overline{F}_1(x))$
- Arbitrary severity df
- Arbitrary dependence structure



$$VAR_t^{+}(\kappa) \sim VAR_t^{1}(\kappa), \quad \kappa \uparrow 1$$

Warning: For general severity df, **the following is not true**:

$$\overline{F}_i(x) = o\left(\overline{F}_1(x)\right) \;\Rightarrow\; VAR_t^{i}(\kappa) = o\left(VAR_t^{1}(\kappa)\right), \quad i = 2,\ldots,d$$

Important SCP Models

Completely dependent SCP Model:

- Losses always occur at the same point in time.
- All cells have identical frequencies: $\lambda := \lambda_1 = 6 \;\; = \lambda_d$
- Severity distributions $F_i(x_i)$ are completely dependent.

Completely independent SCP Model:

- Losses never occur at the same point in time.
- All cells have, in general, different frequencies: $\lambda_1, \lambda_2, 6 \;\; , \lambda_d$
- Severity distributions $F_i(x_i)$ are completely independent.

J

SCP Model With Pareto Severities

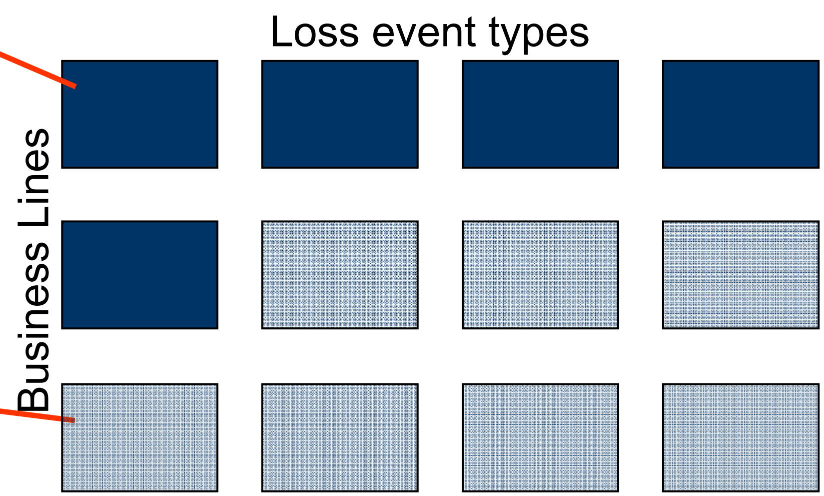
<u>Consider the following example of an SCP Model:</u>

- *b* tail equivalent Pareto cells:

$$\lim_{x\to\infty} \frac{\overline{F}_i(x)}{\overline{F}_1(x)} = \left(\frac{\theta_i}{\theta_1}\right)^{\alpha}, \quad i = 1,\ldots,b$$

- Subdominant Pareto cells:

$$\overline{F}_i(x) = o(\overline{F}_1(x)), \quad i = b+1,\ldots,d$$



➡ Total OpVAR can be analytically calculated…

J

Operational VAR: Violation of Subadditivity

- Dependent-**VAR**$_t$(κ): $$VAR_t^+(\kappa) \sim \sum_{i=1}^{b} VAR_t^i(\kappa)$$
- Independent-**VAR**$_t$(κ): $$VAR_t^+(\kappa) \sim \left(\sum_{i=1}^{b} \left(VAR_t^i(\kappa) \right)^{\alpha} \right)^{1/\alpha}$$
- Example: $b = d = 2;\ \theta_1 = \theta_2 = 1$ and stand alone cell VAR of EUR 100 mn. For α < 1 subadditivity is violated:

α	$VAR_{dependent}$	$VAR_{independent}$
1.2	200	178.2
1.0	200	200.0
0.8	200	237.8

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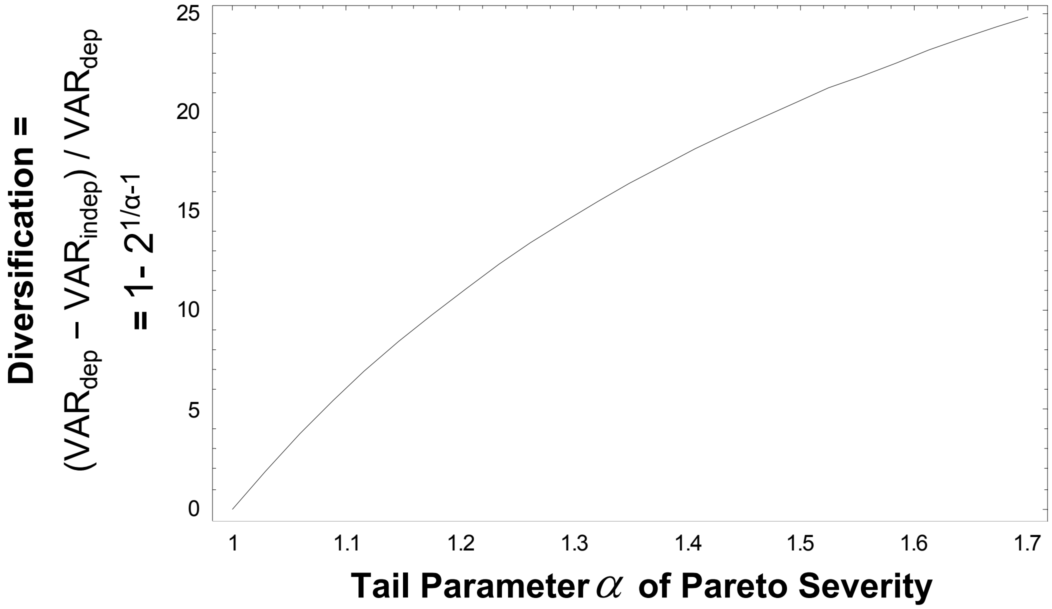
Operational VAR: Impact of Correlation

Dependent-**VAR**$_t$(κ):

Frequency Correlation **= 1**

Independent-**VAR**$_t$(κ):

Frequency Correlation **= 0**



Diversification is very sensitive to the tail parameter of the severity distribution!

J

Multivariate Models for Operational Risk

Klaus Böcker * Claudia Klüppelberg †

Abstract

In Böcker and Klüppelberg (2005) we presented a simple approximation of Op-Var of a single operational risk cell. The present paper derives approximations of similar quality and simplicity for the multivariate problem. Our approach is based on modelling of the dependence structure of different cells via the new concept of a Lévy copula.

JEL Classifications: G18,G39.

Keywords: dependence model, Lévy copula, multivariate dependence, multivariate Lévy processes, operational risk, Pareto distribution, regular variation, subexponential distribution

1 Introduction

The Basel II accord [2], which takes effect by end of the year 2006, imposes new methods of calculating regulatory capital that apply to the banking industry. Besides credit risk, the new accord focuses on operational risk, defined as the risk of losses resulting from inadequate or failed internal processes, people and systems, or from external events. Choosing the advanced measurement approach (AMA), banks can use their own internal modelling technique based on bank-internal and external empirical data.

A required feature of AMA is to allow for explicit correlations between different operational risk events. More precisely, according to Basel II banks should allocate losses to one of eight business lines and to one of seven loss event types. Therefore, the core problem here is the multivariate modelling encompassing all different risk type/business line cells. For this purpose, we consider a d-dimensional compound Poisson process $S =$

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$(S_1(t), S_2(t), \ldots, S_d(t))_{t\geq 0}$ with cadlag (right continuous with left limits) sample paths. Each component has the representation

$$S_i(t) = \sum_{k=1}^{N_i(t)} X_k^i, \quad t \geq 0,$$

where $N_i = (N_i(t))_{t\geq 0}$ is a Poisson process with rate $\lambda_i > 0$ (loss frequency) and $(X_k^i)_{k\in\mathbb{N}}$ is an iid sequence of positive random variables (loss severities), independent of the Poisson process N_i. The bank's total operational risk is then given by the stochastic process

$$S^+(t) := S_1(t) + S_2(t) + \cdots + S_d(t), \quad t \geq 0.$$

Note that S^+ is again a compound Poisson process; cf. Proposition 3.2.

A fundamental question is how the dependence structure between different cells affects the bank's total operational risk. The present literature suggests to model dependence by introducing correlation between the Poisson processes (an example for fixed t can be found in Powojowski, Reynolds and Tuenter [15]), or by using a distributional copula on the random time points where operational loss occurs, or on the number of operational risk events (see Chavez-Demoulin, Embrechts and Nešlehová [7]). In all these approaches, each cell's severities are assumed to be independent and identically distributed (iid) as well as independent of the frequency process. A possible dependence between severities has to be modelled separately, yielding in the end to a rather complicated model. Given the fact that statistical fitting of a high-parameter model seems out of reach by the sparsity of the data, a simpler model is called for.

Our approach has the advantage of modelling dependence in frequency and severity at the same time yielding a model with comparably few parameters. Consequently, with a rather transparent dependence model, we are able to model coincident losses occurring in different cells. From a mathematical point of view, in contrast to the models proposed in Chavez-Demoulin et al. [7], we stay within the class of multivariate Lévy processes, a class of stochastic processes, which has been well studied also in the context of derivatives pricing; see e.g. Cont and Tankov [8].

Since operational risk is only concerned with losses, we restrict ourselves to Lévy processes admitting only positive jumps in every component, hereafter called *spectrally positive Lévy processes.* As a consequence of their independent and stationary increments, Lévy processes can be represented by the *Lévy-Khintchine formula*, which for a d-dimensional spectrally positive Lévy processes S without drift and Gaussian component simplifies to

$$E(e^{i\,(z,S_t)}) = \exp\left\{t \int_{\mathbb{R}_+^d} (e^{i(z,x)} - 1)\,\Pi(dx)\right\}, \quad z \in \mathbb{R}^d,$$

where Π is a measure on $\mathbb{R}^d_+$, called the *Lévy measure* of S, E is the expectation operator, and $(x, y) := \sum_{i=1}^d x_i y_i$ for $x, y \in \mathbb{R}^d$ denotes the inner product.

Whereas the dependence structure in a Gaussian model is well-understood, dependence in the Lévy measure Π is much less obvious. Nevertheless, as Π is independent of t, it suggests itself for modelling the dependence structure between the components of S. Such an approach has been suggested and investigated in Cont and Tankov [8], Kallsen and Tankov [10] and Barndorff-Nielsen and Lindner [1], and essentially models dependence between the jumps of different Lévy processes by means of so-called *Lévy copulas*.

In this paper we invoke Lévy copulas to model the dependence between different operational risk cells. This allows us to gain deep insight into the multivariate behaviour of operational risk defined as a high quantile of a loss distribution and referred to as *operational VaR* (OpVaR). In certain cases, we obtain closed-form approximations for OpVaR and, in this respect, this paper can be regarded as a multivariate extension of Böcker and Klüppelberg [4], where univariate OpVaR has been investigated. In particular, we examine the important cases of dependent and completely independent cells and derive asymptotic closed-form expressions for the corresponding bank's total OpVaR. In doing so, we show that for very heavy-tailed data completely dependent OpVaR, which is asymptotically simply the sum of the single cell VaRs, is even smaller than completely independent OpVaR. Finally, we present upper and lower bounds for total OpVaR in the case of arbitrary dependence structures, exemplified for a Clayton Lévy copula.

2 Preliminaries

2.1 Lévy Processes, Tail Integrals, and Lévy Copulas

Distributional copulas are multivariate uniform distribution functions. They are used for dependence modelling within the context of Sklar's theorem, which states that any multivariate distribution with continuous marginals can be transformed into a multivariate uniform distribution. This concept exploits the fact that distribution functions have values only in $[0, 1]$. In contrast, Lévy measures are in general unbounded on $\mathbb{R}^d$ and may have a non-integrable singularity at 0, which causes problems for the copula idea. Within the class of spectrally positive compound Poisson models, the Lévy measure of the cell process S_i is given by $\Pi_i([0, x)) = \lambda_i P(X^i \leq x)$ for $x \in [0, \infty)$. It follows that the Lévy measure is a finite measure with total mass $\Pi_i([0, \infty)) = \lambda_i$ and therefore in general not a probability measure. Since we are interested in extreme operational losses, we prefer (as is usual in the context of general Lévy process theory) to define a copula for the tail integral. Although we shall mainly work with compound Poisson processes, we formulate definitions and some results and examples for the slightly more general case of spectrally positive Lévy processes.

Definition 2.1. [Tail integral] *Let X be a spectrally positive Lévy process in $\mathbb{R}^d$ with Lévy measure Π. Its* tail integral *is the function $\overline{\Pi} : [0,\infty]^d \to [0,\infty]$ satisfying for $x = (x_1, \dots, x_d)$,*

(1) $\overline{\Pi}(x) = \Pi([x_1,\infty) \times \cdots \times [x_d,\infty))\,, \quad x \in [0,\infty)^d\,,$
where $\overline{\Pi}(0) = \lim_{x_1 \downarrow 0, \dots, x_d \downarrow 0} \Pi([x_1,\infty) \times \cdots \times [x_d,\infty))$
(this limit is finite if and only if X is compound Poisson);

(2) $\overline{\Pi}$ *is equal to 0, if one of its arguments is ∞;*

(3) $\overline{\Pi}(0,\dots,x_i,0,\dots,0) = \overline{\Pi}_i(x_i)$ *for $(x_1,\dots,x_d) \in \mathbb{R}^d_+$, where $\overline{\Pi}_i(x_i) = \Pi_i([x_i,\infty))$ is the tail integral of component i.*

Definition 2.2. [Lévy copula] *A d-dimensional* Lévy copula *of a spectrally positive Lévy process is a measure defining function $\widehat{C} : [0,\infty]^d \to [0,\infty]$ with marginals, which are the identity functions on $[0,\infty]$.*

The following is Sklar's theorem for spectrally positive Lévy processes.

Theorem 2.3. [Cont and Tankov [8], Theorem 5.6] *Let $\overline{\Pi}$ denote the tail integral of a d-dimensional spectrally positive Lévy process, whose components have Lévy measures $\Pi_1,\dots,\Pi_d$. Then there exists a Lévy copula $\widehat{C} : [0,\infty]^d \to [0,\infty]$ such that for all $x_1,\dots,x_d \in [0,\infty]$*

$$\overline{\Pi}(x_1,\dots,x_d) = \widehat{C}(\overline{\Pi}_1(x_1),\dots,\overline{\Pi}_d(x_d)). \tag{2.1}$$

If the marginal tail integrals $\overline{\Pi}_1,\dots,\overline{\Pi}_d$ are continuous, then this Lévy copula is unique. Otherwise, it is unique on $\mathrm{Ran}\overline{\Pi}_1 \times \cdots \times \mathrm{Ran}\overline{\Pi}_d$.
Conversely, if $\widehat{C}$ is a Lévy copula and $\overline{\Pi}_1,\dots,\overline{\Pi}_d$ are marginal tail integrals of spectrally positive Lévy processes, then (2.1) *defines the tail integral of a d-dimensional spectrally positive Lévy process and $\overline{\Pi}_1,\dots,\overline{\Pi}_d$ are tail integrals of its components.*

The following two important Lévy copulas model extreme dependence structures.

Example 2.4. [Complete (positive) dependence]
Let $S(t) = (S_1(t),\dots,S_d(t))$, $t \ge 0$, be a spectrally positive Lévy process with tail integrals $\overline{\Pi}_1,\dots,\overline{\Pi}_d$. Since all jumps are positive, the marginal processes can never be negatively dependent. Complete dependence corresponds to a Lévy copula

$$\widehat{C}_{\|}(x) = \min(x_1,\dots,x_d)\,,$$

implying for the tail integral of S

$$\overline{\Pi}(x_1,\ldots,x_d) = \min(\overline{\Pi}_1(x_1),\ldots,\overline{\Pi}_d(x_d))$$

with all mass concentrated on $\{x \in [0,\infty)^d : \overline{\Pi}_1(x_1) = \cdots = \overline{\Pi}_d(x_d)\}$. □

Example 2.5. [Independence]
Let $S(t) = (S_1(t),\ldots,S_d(t))$, $t \geq 0$, be a spectrally positive Lévy process with tail integrals $\overline{\Pi}_1,\ldots,\overline{\Pi}_d$. The marginal processes are independent if and only if they never jump together, i.e. the Lévy measure Π of S can be decomposed into

$$\Pi(A) = \Pi_1(A_1) + \cdots + \Pi_d(A_d), \qquad A \in [0,\infty)^d \tag{2.2}$$

with $A_1 = \{x_1 \in [0,\infty) : (x_1,0,\ldots,0) \in A\},\ldots,A_d = \{x_d \in [0,\infty) : (0,\ldots,x_d) \in A\}$. Obviously, the support of Π are the coordinate axes. Equation (2.2) implies for the tail integral of S

$$\overline{\Pi}(x_1,\ldots,x_d) = \overline{\Pi}_1(x_1)\,1_{x_2=\cdots=x_d=0} + \cdots + \overline{\Pi}_d(x_d)\,1_{x_1=\cdots=x_{d-1}=0}\,.$$

It follows that the independence copula for spectrally positive Lévy processes is given by

$$\widehat{C}_\perp(x) = x_1\,1_{x_2=\cdots=x_d=\infty} + \cdots + x_d\,1_{x_1=\cdots=x_{d-1}=\infty}\,.$$

□

2.2 Subexponentiality and Regular Variation

As in Böcker and Klüppelberg [4], we work within the class of subexponential distributions to model high severity losses. For more details on subexponential distributions and related classes see Embrechts et al. [9], Appendix A3.

Definition 2.6. [Subexponential distributions] *Let $(X_k)_{k\in\mathbb{N}}$ be iid random variables with distribution function F. Then F (or sometimes $\overline{F}$) is said to be a* subexponential distribution function ($F \in \mathcal{S}$) *if*

$$\lim_{x\to\infty} \frac{P(X_1 + \cdots + X_n > x)}{P(\max(X_1,\ldots,X_n) > x)} = 1 \quad \textit{for some (all) } n \geq 2.$$

The interpretation of subexponential distributions is therefore that their iid sum is likely to be very large because of one of the terms being very large. The attribute *subexponential* refers to the fact that the tail of a subexponential distribution decays slower than any exponential tail, i.e. the class $\mathcal{S}$ consists of heavy-tailed distributions and is therefore appropriate to describe typical operational loss data. Important subexponential distributions are Pareto, lognormal and Weibull (with shape parameter less than 1).

As a useful semiparametric class of subexponential distributions, we introduce distributions with polynomially decreasing tail.

Definition 2.7. [Regularly varying distribution tails] *Let X be a positive random variable with distribution tail $\overline{F}(x) := 1 - F(x) = P(X > x)$ for $x > 0$. If for some $\alpha \geq 0$,*

$$\lim_{t\to\infty} \frac{\overline{F}(xt)}{\overline{F}(t)} = x^{-\alpha}, \quad x > 0,$$

then $\overline{F}$ is called regularly varying with index $-\alpha$*, denoted by $\overline{F} \in \mathcal{R}_{-\alpha}$.*
The quantity α is also called the tail index *of F.*
Finally, we define $\mathcal{R} := \cup_{\alpha\geq 0}\mathcal{R}_{-\alpha}$.

Some remarks are appropriate. First, as already mentioned, $\mathcal{R} \subset \mathcal{S}$. Second, regularly varying distribution functions have representation $\overline{F}(x) = x^{-\alpha}L(x)$ for $x \geq 0$, where L is a *slowly varying function* ($L \in \mathcal{R}_0$) satisfying $\lim_{t\to\infty} L(xt)/L(t) = 1$ for all $x > 0$. Typical examples are functions, which converge to a positive constant or are logarithmic as e.g. $L(\cdot) = \ln(\cdot)$. Third, the classes $\mathcal{S}$ and $\mathcal{R}_{-\alpha}$, $\alpha \geq 0$, are closed with respect to *tail-equivalence*, which for two distribution functions (or also tail integrals) is defined as $\lim_{x\to\infty} \overline{F}(x)/\overline{G}(x) = c$ for $c \in (0,\infty)$. Finally, we introduce the notation $\overline{F}(x) \sim \overline{G}(x)$ as $x \to \infty$, meaning that the quotient of right hand and left hand side tends to 1; i.e. $\lim_{x\to\infty} \overline{G}(x)/\overline{F}(x) = 1$.

Distributions in $\mathcal{S}$ but not in $\mathcal{R}$ include the heavy-tailed Weibull distribution and the lognormal distribution. Their tail decreases faster than tails in $\mathcal{R}$, but less fast than an exponential tail. The following definition will be useful.

Definition 2.8. [Rapidly varying distribution tails] *Let X be a positive random variable with distribution tail $\overline{F}(x) := 1 - F(x) = P(X > x)$ for $x > 0$. If*

$$\lim_{t\to\infty} \frac{\overline{F}(xt)}{\overline{F}(t)} = \begin{cases} 0, & \text{if } x > 1, \\ \infty & \text{if } 0 < x < 1. \end{cases}$$

then $\overline{F}$ is called rapidly varying*, denoted by $\overline{F} \in \mathcal{R}_\infty$.*

2.3 Recalling the Single Cell Model

Now we are in the position to introduce an LDA model based on subexponential severities. We begin with the univariate case. Later, when we consider multivariate models, each of its d operational risk processes will follow the univariate model defined below.

Definition 2.9. [Subexponential compound Poisson (SCP) model]

(1) The severity process.
The severities $(X_k)_{k\in\mathbb{N}}$ are positive iid random variables with distribution function $F \in \mathcal{S}$ describing the magnitude of each loss event.

(2) The frequency process.
The number $N(t)$ *of loss events in the time interval* $[0,t]$ *for* $t \geq 0$ *is random, where* $(N(t))_{t\geq 0}$ *is a homogenous Poisson process with intensity* $\lambda > 0$. *In particular,*

$$P(N(t)=n) = p_t(n) = e^{-\lambda t}\,\frac{(\lambda t)^n}{n!}, \quad n \in \mathbb{N}_0\,.$$

(3) *The severity process and the frequency process are assumed to be independent.*

(4) The aggregate loss process.
The aggregate loss $S(t)$ *in* $[0,t]$ *constitutes a process*

$$S(t) = \sum_{k=1}^{N(t)} X_k\,, \quad t \geq 0\,.$$

Of main importance in the context of operational risk is the *aggregate loss distribution function*, given by

$$G_t(x) = P(S(t) \leq x) = \sum_{n=0}^{\infty} p_t(n)\,F^{n*}(x), \quad x \geq 0, \quad t \geq 0\,, \tag{2.3}$$

with

$$p_t(n) = P(N_t = n) = e^{-\lambda t}\,\frac{(\lambda t)^n}{n!}, \quad n \in \mathbb{N}_0\,,$$

and $F(\cdot) = P(X_k \leq \cdot)$ is the distribution function of X_k, and $F^{n*}(\cdot) = P(\sum_{k=1}^n X_k \leq \cdot)$ is the n-fold convolution of F with $F^{1*} = F$ and $F^{0*} = I_{[0,\infty)}$.

Now, OpVaR is just a quantile of G_t. The following defines the OpVar of a single cell process, the so-called *stand alone* VaR.

Definition 2.10. [Operational VaR (OpVaR)] *Suppose* G_t *is a loss distribution function according to eq. (2.3). Then,* operational VaR *up to time* t *at confidence level* κ, $\mathrm{VaR}_t(\kappa)$, *is defined as its* κ*-quantile*

$$\mathrm{VaR}_t(\kappa) = G_t^{\leftarrow}(\kappa)\,, \quad \kappa \in (0,1)\,,$$

where $G_t^{\leftarrow}(\kappa) = \inf\{x \in \mathbb{R} : \; G_t(x) \geq \kappa\}$, $0 < \kappa < 1$, *is the (left continuous) generalized inverse of* G_t. *If* G_t *is strictly increasing and continuous, we may write* $\mathrm{VaR}_t(\kappa) = G_t^{-1}(\kappa)$.

In general, $G_t(x)$—and thus also OpVaR—cannot be analytically calculated so that one depends on techniques like Panjer recursion, Monte Carlo simulation, and fast Fourier transform (FFT), see e.g. Klugman et al. [11]. Recently, based on the asymptotic identity $\overline{G}_t(x) \sim \lambda\, t\overline{F}(x)$ as $x \to \infty$ for subexponential distributions, Böcker and Klüppelberg [4] have shown that for a wide class of LDA models closed-form approximations for OpVaR at high confidence levels are available. For a more natural definition in the context of high quantiles we express $\mathrm{VaR}_t(\kappa)$ in terms of the tail $\overline{F}(\cdot)$ instead of $F(\cdot)$. This can easily be achieved by noting that $1/\overline{F}$ is increasing, hence,

$$\begin{aligned} F^{\leftarrow}(\kappa) &= \inf\{x \in \mathbb{R} : \; F(x) \geq \kappa\} \\ &= \inf\{x \in \mathbb{R} : \; 1/\overline{F}(x) \geq 1/(1-\kappa)\} \\ &=: \left(\frac{1}{\overline{F}}\right)^{\leftarrow}\left(\frac{1}{1-\kappa}\right), \quad 0 < \kappa < 1 \,. \end{aligned} \tag{2.4}$$

In [4] we have shown that

$$G_t^{\leftarrow}(\kappa) = F^{\leftarrow}\left(1 - \frac{1-\kappa}{\lambda t}(1+o(1))\right), \quad \kappa \uparrow 1 \,, \tag{2.5}$$

or, equivalently using (2.4),

$$\left(\frac{1}{\overline{G_t}}\right)^{\leftarrow}\left(\frac{1}{1-\kappa}\right) = \left(\frac{1}{\overline{F}}\right)^{\leftarrow}\left(\frac{\lambda t}{1-\kappa}(1+o(1))\right), \quad \kappa \uparrow 1 \,. \tag{2.6}$$

In the present paper we shall restrict ourselves to situations, where the right-hand side of (2.5) is asymptotically equivalent to $F^{\leftarrow}\big(1 - \frac{1-\kappa}{\lambda t}\big)$ as $\kappa \uparrow 1$. That this is not always the case for $F \in \mathcal{S}$ shows the following example.

Example 2.11. Consider $(1/\overline{F})^{\leftarrow}(y) = \exp(y + y^{1-\varepsilon})$ for some $0 < \varepsilon < 1$ with $y = 1/(1-\kappa)$, i.e. $\kappa \uparrow 1$ equivalent to $y \to \infty$. Then $(1/\overline{F})^{\leftarrow}(y) = \exp(y(1+o(1))$, but $(1/\overline{F})^{\leftarrow}(y)/e^y = \exp(y^{1-\varepsilon}) \to \infty$ as $y \to \infty$. This situation typically occurs, when $\overline{F} \in \mathcal{R}_0$, i.e. for extremely heavy-tailed models. □

The reason is given by the following equivalences, which we will often use throughout this paper:

Proposition 2.12. *(1)* [Regular variation] *Let* $\alpha > 0$. *Then*
(i) $\overline{F} \in \mathcal{R}_{-\alpha} \quad \Leftrightarrow \quad (1/\overline{F})^{\leftarrow} \in \mathcal{R}_{1/\alpha}$,
(ii) $\overline{F}(x) = x^{-\alpha}L(x)$ *for* $x \geq 0 \quad \Leftrightarrow \quad (1/\overline{F})^{\leftarrow}(z) = z^{1/\alpha}\widetilde{L}(z)$ *for* $z \geq 0$,
where L *and* $\widetilde{L}$ *are slowly varying functions,*
(iii) $\overline{F}(x) \sim \overline{G}(x)$ *as* $x \to \infty \quad \Leftrightarrow \quad (1/\overline{F})^{\leftarrow}(z) \sim (1/\overline{G})^{\leftarrow}(z)$ *as* $z \to \infty$.

(2) [Rapid variation] *If* $\overline{F}, \overline{G} \in \mathcal{R}_\infty$ *such that* $\overline{F}(x) \sim \overline{G}(x)$ *as* $x \to \infty$, *then* $(1/\overline{F})^{\leftarrow}(z) \sim (1/\overline{G})^{\leftarrow}(z)$ *as* $z \to \infty$.

Proof. (1) Proposition 1.5.15 of Bingham, Goldie and Teugels [3] ensures that regular variation of $1/\overline{F}$ is equivalent to regular variation of its (generalised) inverse and provides the representation. Proposition 0.8(vi) of Resnick [16] gives the asymptotic equivalence.
(2) Theorem 2.4.7 of [3](ii) applied to $1/\overline{F}$ ensures that $(1/\overline{F})^{\leftarrow} \in \mathcal{R}_0$. Furthermore, tail

equivalence of F and G implies that $(1/\overline{F})^{\leftarrow}(z) = (1/\overline{G})^{\leftarrow}(z(1+o(1))) = (1/\overline{G})^{\leftarrow}(z)(1+o(1))$ as $z \to \infty$, where we have used that the convergence in Definition 2.7 is locally uniformly. $\square$

Theorem 2.13. [Analytical OpVaR for the SCP model] *Consider the SCP model.*
(i) *If $\overline{F} \in \mathcal{S} \cap (\mathcal{R} \cup \mathcal{R}_\infty)$, then* $\mathrm{VaR}_t(\kappa)$ *is asymptotically given by*

$$\mathrm{VaR}_t(\kappa) = \left(\frac{1}{\overline{G}_t}\right)^{\leftarrow} \left(\frac{1}{1-\kappa}\right) \sim F^{\leftarrow}\left(1 - \frac{1-\kappa}{\lambda t}\right), \quad \kappa \uparrow 1. \tag{2.7}$$

(ii) *The severity distribution tail belongs to $\mathcal{R}_{-\alpha}$ for $\alpha > 0$, i.e. $\overline{F}(x) = x^{-\alpha} L(x)$ for $x \geq 0$ and some slowly varying function L if and only if*

$$\mathrm{VaR}_t(\kappa) \sim \left(\frac{\lambda t}{1-\kappa}\right)^{1/\alpha} \widetilde{L}\left(\frac{1}{1-\kappa}\right), \quad \kappa \uparrow 1, \tag{2.8}$$

where $\widetilde{L}\left(\frac{1}{1-\cdot}\right) \in \mathcal{R}_0$.

Proof. (i) is a consequene of Böcker and Klüppelberg [4] in combination with Proposition 2.12.
(ii) By Definition 2.10, $\mathrm{VaR}_t(\kappa) = G^{\leftarrow}(\kappa)$. In our SCP model we have $\overline{G}_t(x) \sim \lambda t \overline{F}(x)$ as $x \to \infty$. From Proposition 2.12 it follows that

$$\left(\frac{1}{\overline{G}_t}\right)^{\leftarrow} \left(\frac{1}{1-\kappa}\right) \sim \left(\frac{1}{\overline{F}}\right)^{\leftarrow} \left(\frac{\lambda t}{1-\kappa}\right) = \left(\frac{\lambda t}{1-\kappa}\right)^{1/\alpha} \widetilde{L}\left(\frac{\lambda t}{1-\kappa}\right), \quad \kappa \uparrow 1,$$

and the result follows. $\square$

We refrain from giving more information on the relationship between L and $\widetilde{L}$ (which can be found in [3]) as it is rather involved and plays no role in our paper. When such a model is fitted statistically, then L and $\widetilde{L}$ are usually replaced by constants; see Embrechts et al. [9], Chapter 6. In that case $L \equiv \theta^\alpha$, resulting in $\widetilde{L} \equiv \theta$ as in the following example. To indicate that the equivalence of Theorem 2.13(ii) does not extend to subexponential distribution tails in $\mathcal{R}_\infty$ we refer to Example 3.9.

We can now formulate the analytical VaR theorem for subexponential severity tails. A precise result can be obtained for Pareto distributed severities. Pareto's law is the prototypical parametric example for a heavy tailed distribution and suitable for operational risk modelling, see e.g. Moscadelli [14].

Example 2.14. [Poisson-Pareto LDA]
The *Poisson-Pareto LDA* is an SCP model, where the severities are Pareto distributed with

$$\overline{F}(x) = \left(1 + \frac{x}{\theta}\right)^{-\alpha}, \quad x > 0,$$

with parameters $\alpha, \theta > 0$. Here, OpVaR can be calculated explicitly and satisfies

$$\mathrm{VaR}_t(\kappa) \sim \theta \left[\left(\frac{\lambda\, t}{1-\kappa} \right)^{1/\alpha} - 1 \right] \sim \theta \left(\frac{\lambda\, t}{1-\kappa} \right)^{1/\alpha} , \quad \kappa \uparrow 1 . \tag{2.9}$$

□

3 A Multivariate Loss Distribution Model

3.1 Multivariate LDA Models by means of Lévy Copulas

The SCP model of the previous section can be used for estimating OpVaR of a single cell, sometimes referred to as the cell's *stand alone* OpVaR. Then, a first approximation to the bank's total OpVaR is obtained by summing up all different stand alone VaR numbers. Indeed, the Basel committee requires banks to sum up all their different operational risk estimates unless sound and robust correlation estimates are available, cf. [2], paragraph 669(d). Moreover, this "simple-sum VaR" is often interpreted as an upper bound for total OpVaR, with the implicit understanding that every other (realistic) cell dependence model necessarily reduces overall operational risk. However, we will see in Section 3.1.1 that simple-sum VaR may even underestimate total OpVar when severity data is very heavy-tailed, which in practice is possible, see e.g. Moscadelli [14]. Therefore, to obtain a more accurate and reliable result, one needs—besides more extensive internal and external empirical loss data— more general models for multivariate operational risk.

Definition 3.1. [Multivariate SCP model] *The* multivariate SCP model *consists of:*

(1) Cell processes.
All operational risk cells, indexed by $i = 1, \ldots, d$, are described by an SCP model with aggregate loss process S_i, subexponential severity distribution function F_i and Poisson parameter $\lambda_i > 0$, respectively.

(2) Dependence structure.
The dependence between different cells is modelled by a Lévy copula. More precisely, let $\overline{\Pi}_i : [0,\infty) \to [0,\infty)$ be the tail integral associated with S_i, i.e. $\overline{\Pi}_i(\cdot) = \lambda_i \overline{F}_i(\cdot)$ for $i = 1, \ldots, d$, and let $\widehat{C} : [0,\infty)^d \to [0,\infty)$ be a Lévy copula. Then

$$\overline{\Pi}(x_1, \ldots, x_d) = \widehat{C}(\overline{\Pi}_1(x_1), \ldots, \overline{\Pi}_d(x_d))$$

defines the tail integral of the d-dimensional compound Poisson process $S = (S_1, \ldots, S_d)$.

(3) Total aggregate loss process.
The bank's total aggregate loss process *is defined as*

$$S^+(t) = S_1(t) + S_2(t) + \cdots + S_d(t) , \qquad t \geq 0$$

with tail integral

$$\overline{\Pi}^{+}(z) = \Pi(\{(x_1, \dots, x_d) \in [0,\infty)^d : \sum_{i=1}^{d} x_i \geq z\}), \quad z \geq 0. \tag{3.1}$$

The following result states an important property of the multivariate SCP model.

Proposition 3.2. *Consider the multivariate SCP model of Definition 3.1. Its total aggregate loss process S^+ is compound Poisson with frequency parameter*

$$\lambda^+ = \lim_{z \downarrow 0} \overline{\Pi}^{+}(z)$$

and severity distribution

$$F^+(z) = 1 - \overline{F}^{+}(z) = 1 - \frac{\overline{\Pi}^{+}(z)}{\lambda^+}, \quad z \geq 0.$$

Proof. For any compound Poisson process with intensity $\lambda > 0$ and only positive jumps with distribution function F the tail integral of the Lévy measure is given by $\overline{\Pi}(x) = \lambda \overline{F}(x)$, $x > 0$. Consequently, $\lambda = \overline{\Pi}(0)$ and $\overline{F}(x) = \overline{\Pi}(x)/\lambda$. We apply this relation to the compound Poisson process S^+. □

Note that S^+ does not necessarily define a one dimensional SCP model because, in general, F^+ is not subexponential. However, if $F^+ \in \mathcal{S} \cap (\mathcal{R} \cup \mathcal{R}_\infty)$, we can apply (2.7) to estimate total OpVaR, which shall now be defined precisely.

Definition 3.3. [Total OpVaR] *Consider the multivariate SCP model of Definition 3.1. Then,* total OpVaR *up to time t at confidence level κ is the κ-quantile of the total aggregate loss distribution $G_t^+(\cdot) = P(S^+(t) \leq \cdot)$:*

$$\mathrm{VaR}_t^+(\kappa) = G_t^{+\leftarrow}(\kappa), \quad \kappa \in (0,1),$$

with $G_t^{+\leftarrow}(\kappa) = \inf\{z \in \mathbb{R} : \; G_t^+(z) \geq \kappa\}$ for $0 < \kappa < 1$.

Our goal in this paper is to investigate multivariate SCP models. Although for general dependence structures no closed-form solutions for OpVaR will be available, we can obtain some useful approximations and valuable insights to multivariate operational risk.

To derive our first important result, assume that the severity distribution F^+ of Proposition 3.2 is in $\mathcal{S} \cap (\mathcal{R} \cup \mathcal{R}_\infty)$ so that Theorem 2.13 applies, in particular, meaning that total OpVaR asymptotically depends only on the *expected* frequency of losses λ^+. As a consequence thereof, all dependence models that are solely based on dependencies between the frequency processes have (asymptotically) no impact on total OpVaR because expectation is not affected by the dependence structure itself.

Our next result is relevant in situations, where one severity distribution has a considerably heavier tail than the others. Our proof is similar to the proof of the corresponding result for random variables given in Klüppelberg, Lindner and Maller [12], Section 5, Lemma 2. Note also that the result and the proof not only holds for compound Poisson models but also for more general spectrally positive Lévy processes because a possible singularity of the tail integral in 0 is of no consequence.

Theorem 3.4. *Consider a multivariate SCP model and suppose that $\overline{F}_1 \in \mathcal{R}_{-\alpha}$. Furthermore, assume that for all $i = 2, \dots, d$ the integrability condition*

$$\int_{x \geq 1} x^{\delta}\, \Pi_i(dx) < \infty \tag{3.2}$$

for some $\delta > \alpha$ is satisfied. Then

$$\lim_{z\to\infty} \frac{\overline{\Pi}^{+}(z)}{\overline{\Pi}_1(z)} = 1\,. \tag{3.3}$$

Moreover,

$$\mathrm{VaR}_t^{+}(\kappa) \sim \mathrm{VaR}_t^{1}(\kappa)\,, \qquad \kappa \uparrow 1\,,$$

i.e. total OpVaR is asymptotically dominated by the stand alone OpVaR of the first cell.

Proof. We first show that (3.3) holds. From equation (3.2) it follows that for $i = 2, \dots, d$

$$\lim_{z\to\infty} z^{\delta}\, \overline{\Pi}_i(z) = 0\,. \tag{3.4}$$

Since $\alpha < \delta$, we obtain from regular variation for some slowly varying function L, invoking (3.4),

$$\lim_{z\to\infty} \frac{\overline{\Pi}_i(z)}{\overline{\Pi}_1(z)} = \lim_{z\to\infty} \frac{z^{\delta}\overline{\Pi}_i(z)}{z^{\delta-\alpha}L(z)} = 0\,, \quad i = 2, \dots, d\,,$$

because the numerator tends to 0 and the denominator to ∞. (Recall that $z^{\varepsilon}L(z) \to \infty$ as $z \to \infty$ for all $\varepsilon > 0$ and $L \in \mathcal{R}_0$.)

We proceed by induction. For $d = 2$ we have by a geometric argument

$$\overline{\Pi}_2^{+}(z) := \overline{\Pi}^{+}(z) \leq \overline{\Pi}_1(z(1-\varepsilon)) + \overline{\Pi}_2(z\,\varepsilon), \quad z > 0, \quad 0 < \varepsilon < 1.$$

It then follows that

$$\limsup_{z\to\infty} \frac{\overline{\Pi}_2^{+}(z)}{\overline{\Pi}_1(z)} \leq \lim_{z\to\infty} \frac{\overline{\Pi}_1(z(1-\varepsilon))}{\overline{\Pi}_1(z)} + \lim_{z\to\infty} \frac{\overline{\Pi}_2(z\,\varepsilon)}{\overline{\Pi}_1(z\,\varepsilon)} \frac{\overline{\Pi}_1(z\,\varepsilon)}{\overline{\Pi}_1(z)} = (1-\varepsilon)^{-\alpha}\,. \tag{3.5}$$

Similarly, $\overline{\Pi}_2^+(z) \geq \overline{\Pi}_1((1+\varepsilon)z)$ for every $\varepsilon > 0$. Therefore,

$$\liminf_{z\to\infty} \frac{\overline{\Pi}_2^+(z)}{\overline{\Pi}_1(z)} \geq \lim_{z\to\infty} \frac{\overline{\Pi}_1((1+\varepsilon)z)}{\overline{\Pi}_1(z)} = (1+\varepsilon)^{-\alpha}. \tag{3.6}$$

Assertion (3.3) follows for $\overline{\Pi}_2^+$ from (3.5) and (3.6). This implies that $\overline{\Pi}_2^+ \in \mathcal{R}_\alpha$. Now replace $\overline{\Pi}_1$ by $\overline{\Pi}_2^+$ and $\overline{\Pi}_2^+$ by $\overline{\Pi}_3^+$ and proceed as above to obtain (3.3) for general dimension d. Finally, Theorem 2.13 applies giving

$$\mathrm{VaR}_t^+(\kappa) \sim F_1^{\leftarrow}\left(1 - \frac{1-\kappa}{\lambda_1 t}\right) = \mathrm{VaR}_t^1(\kappa), \qquad \kappa \uparrow 1. \qquad \square$$

Hence, for arbitrary dependence structures, when the severity of *one* cell has regularly varying tail dominating those of all other cells, total OpVaR is tail-equivalent to the OpVaR of the dominating cell. This implies that the bank's total loss at high confidence levels is likely to be due to one big loss occurring in the first cell rather than an accumulation of losses of different cells regardless of the dependence structure.

From our equivalence results of Proposition 2.12 and Theorem 2.13, this is not a property of SCP models in general. We shall see in Example 3.9 below that the following does not hold in general for $x \to \infty$ (equivalently $\kappa \uparrow 1$):

$$\overline{F}_i(x) = o(\overline{F}_1(x)) \quad \Longrightarrow \quad \mathrm{VaR}_t^i(\kappa) = o(\mathrm{VaR}_t^1(\kappa)), \quad i = 2, \ldots, d.$$

We now study two very basic multivariate SCP models in more detail, namely the completely dependent and the independent one. Despite their extreme dependence structure, both models provide interesting and valuable insight into multivariate operational risk.

3.1.1 Multivariate SCP Model with Completely Dependent Cells

Consider a multivariate SCP model and assume that its cell processes S_i, $i = 1, \ldots, d$, are completely positively dependent. In the context of Lévy processes this means that they always jump together, implying that also the expected number of jumps per unit time of all cells, i.e. the intensities λ_i, must be equal,

$$\lambda := \lambda_1 = \cdots = \lambda_d. \tag{3.7}$$

The severity distributions F_i, however, can be different. Indeed, from Example 2.4 we infer that in the case of complete dependence, all Lévy mass is concentrated on

$$\{(x_1, \ldots, x_d) \in [0,\infty)^d : \overline{\Pi}_1(x_1) = \cdots = \overline{\Pi}_d(x_d)\},$$

or, equivalently,

$$\{(x_1, \ldots, x_d) \in [0, \infty)^d : F_1(x_1) = \cdots = F_d(x_d)\}. \tag{3.8}$$

Until further notice, we assume for simplicity that all severity distributions F_i are strictly increasing and continuous so that $F_i^{-1}(q)$ exists for all $q \in [0,1)$. Together with (3.8), we can express the tail integral of S^+ in terms of the marginal $\overline{\Pi}_1$,

$$\begin{aligned}
\overline{\Pi}^+(z) &= \Pi(\{(x_1, \ldots, x_d) \in [0, \infty)^d : \sum_{i=1}^d x_i \geq z\}) \\
&= \Pi_1(\{x_1 \in [0, \infty) : x_1 + \sum_{i=2}^d F_i^{-1}(F_1(x_1)) \geq z\}), \quad z \geq 0.
\end{aligned}$$

Set $H(x_1) := x_1 + \sum_{i=2}^d F_i^{-1}(F_1(x_1))$ for $x_1 \in [0, \infty)$ and note that it is strictly increasing and therefore invertible. Hence,

$$\overline{\Pi}^+(z) = \Pi_1(\{x_1 \in [0, \infty) : x_1 \geq H^{-1}(z)\}) = \overline{\Pi}_1\left(H^{-1}(z)\right), \quad z \geq 0. \tag{3.9}$$

Now we can derive an asymptotic expression for total OpVaR.

Theorem 3.5. [OpVaR for the completely dependent SCP model] *Consider a multivariate SCP model with completely dependent cell processes $S_1, \ldots, S_d$ and strictly increasing and continuous severity distributions F_i. Then, S^+ is compound Poisson with parameters*

$$\lambda^+ = \lambda \quad \text{and} \quad \overline{F}^+(\cdot) = \overline{F}_1\left(H^{-1}(\cdot)\right). \tag{3.10}$$

If furthermore $\overline{F}^+ \in \mathcal{S} \cap (\mathcal{R} \cup \mathcal{R}_\infty)$, total OpVaR is asymptotically given by

$$\mathrm{VaR}_t^+(\kappa) \sim \sum_{i=1}^d \mathrm{VaR}_t^i(\kappa), \quad \kappa \uparrow 1, \tag{3.11}$$

where $\mathrm{VaR}_t^i(\kappa)$ denotes the stand alone OpVaR of cell i.

Proof. Expression (3.10) immediately follows from (3.7) and (3.9),

$$\lambda^+ = \lim_{z \to 0} \overline{\Pi}^+(z) = \lim_{z \to 0} \lambda \overline{F}_1\left(H^{-1}(z)\right) = \lambda \overline{F}_1\left(\lim_{z \to 0} H^{-1}(z)\right) = \lambda.$$

If $\overline{F}^+ \in \mathcal{S} \cap (\mathcal{R} \cup \mathcal{R}_\infty)$, we may use (2.7) and the definition of H to obtain

$$\begin{aligned}
\mathrm{VaR}_t^+(\kappa) &\sim H\left[F_1^{-1}\left(1 - \frac{1-\kappa}{\lambda t}\right)\right] = F_1^{-1}\left(1 - \frac{1-\kappa}{\lambda t}\right) + \cdots + F_d^{-1}\left(1 - \frac{1-\kappa}{\lambda t}\right) \\
&\sim \mathrm{VaR}_t^1(\kappa) + \cdots + \mathrm{VaR}_t^d(\kappa), \quad \kappa \uparrow 1.
\end{aligned}$$

$\square$

Theorem 3.5 states that for the completely dependent SCP model, total asymptotic OpVaR is simply the sum of the asymptotic stand alone cell OpVaRs. Recall that this is similar to the new proposals of Basel II, where the standard procedure for calculating capital charges for operational risk is just the simple-sum VaR. Or stated another way, regulators implicitly assume complete dependence between different cells, meaning that losses within different business lines or risk categories always happen at the same instants of time. This is often considered as the worst case scenario, which, however, in the heavy-tailed case can be grossly misleading. We shall come back to this point later; see in particular Table 3.14.

The following example describes another regime for completely depenendent cells.

Example 3.6. [Identical severity distributions]
Assume that all cells have identical severity distributions, i.e. $F := F_1 = \ldots = F_d$. In this case we have $H(x_1) = d\,x_1$ for $x_1 \geq 0$ and, therefore,

$$\overline{\Pi}^+(z) = \lambda\,\overline{F}\left(\frac{z}{d}\right), \quad z \geq 0\,.$$

If furthermore $\overline{F} \in \mathcal{S} \cap (\mathcal{R} \cup \mathcal{R}_\infty)$, it follows that $\overline{F}^+(\cdot) = \overline{F}(\cdot\,/d)$ is, and we obtain

$$\mathrm{VaR}_t^+(\kappa) \sim d\,\overline{F}\left(1 - \frac{1-\kappa}{\lambda\,t}\right), \quad \kappa \uparrow 1\,.$$

$\square$

We can derive very precise asymptotics in the case of dominating regularly varying severities.

Proposition 3.7. *Assume that the conditions of Theorem 3.5 hold. Assume further that* $\overline{F}_1 \in \mathcal{R}_{-\alpha}$ *with* $\alpha > 0$ *and that for all* $i = 2, \ldots, d$ *there exist* $c_i \in [0, \infty)$ *such that*

$$\lim_{x\to\infty} \frac{\overline{F}_i(x)}{\overline{F}_1(x)} = c_i\,. \tag{3.12}$$

Assume that $c_i \neq 0$ *for* $2 \leq i \leq b \leq d$ *and* $c_i = 0$ *for* $i \leq b+1 \leq d$. *For* $\overline{F}_1(x) = x^{-\alpha}L(x)$, $x \geq 0$, *let* $\widetilde{L}$ *be the function as in Theorem 2.13(ii). Then*

$$\mathrm{VaR}_t^+(\kappa) \;\sim\; \sum_{i=1}^{b} c_i^{1/\alpha}\,\mathrm{VaR}_t^1(\kappa) \sim \sum_{i=1}^{b} c_i^{1/\alpha}\left(\frac{\lambda\,t}{1-\kappa}\right)^{1/\alpha}\widetilde{L}\left(\frac{1}{1-\kappa}\right), \quad \kappa \uparrow 1\,.$$

Proof. From Theorem 2.13(ii) we know that

$$\mathrm{VaR}_t^1(\kappa) \sim \left(\frac{\lambda\,t}{1-\kappa}\right)^{1/\alpha}\widetilde{L}\left(\frac{1}{1-\kappa}\right), \quad \kappa \uparrow 1\,,$$

where $\widetilde{L}\left(\frac{1}{1-\cdot}\right) \in \mathcal{R}_0$. Note: If all $c_i = 0$ holds for $i = 2, \ldots, d$ then Theorem 3.4 applies. So assume that $c_i \neq 0$ for $2 \leq i \leq b$. From (3.12) and Resnick [16], Proposition 0.8(vi), we get $F_i^{\leftarrow}(1 - \frac{1}{z}) \sim c_i^{1/\alpha} F_1^{\leftarrow}(1 - \frac{1}{z})$ as $z \to \infty$ for $i = 1, \ldots, d$. This yields for $x_1 \to \infty$

$$\begin{aligned} H(x_1) &= x_1 + \sum_{i=2}^{d} F_i^{-1}(1 - \overline{F}_1(x_1)) \\ &= x_1 + \sum_{i=2}^{d} c_i^{1/\alpha} F_1^{-1}\left(1 - \overline{F}_1(x_1)\right)(1 + o_i(1)) \\ &= x_1 \sum_{i=1}^{b} c_i^{1/\alpha}\,(1 + o(1))\,, \end{aligned}$$

where we have $c_1 = 1$. Defining $C := \sum_{i=1}^{b} c_i^{1/\alpha}$, then $H(x_1) \sim C x_1$ as $x_1 \to \infty$, and hence $H^{-1}(z) \sim z/C$ as $z \to \infty$, which implies by (3.9) and regular variation of $\overline{F}_1$

$$\overline{\Pi}^{+}(z) = \overline{\Pi}_1(H^{-1}(z)) \sim \lambda\,\overline{F}_1(z/C) \sim \lambda\, C^{\alpha}\,\overline{F}_1(z)\,, \quad z \to \infty\,.$$

Obviously, $\overline{F}^{+}(z) = C^{\alpha}\,\overline{F}_1(z) \in \mathcal{R}_{-\alpha}$ and Theorem 3.5 applies. By (2.8) together with the fact that all summands from index $b+1$ on are of lower order, (3.11) reduces to

$$\begin{aligned} \mathrm{VaR}_t^{+}(\kappa) &\sim F_1^{\leftarrow}\left(1 - \frac{1-\kappa}{\lambda\, t}\right) + \cdots + F_b^{\leftarrow}\left(1 - \frac{1-\kappa}{\lambda\, t}\right) \\ &\sim F_1^{\leftarrow}\left(1 - \frac{1-\kappa}{\lambda\, t\, C^{\alpha}}\right) \\ &\sim \sum_{i=1}^{b} c_i^{1/\alpha}\left(\frac{\lambda\, t}{1-\kappa}\right)^{1/\alpha} \widetilde{L}\left(\frac{1}{1-\kappa}\right), \quad \kappa \uparrow 1\,. \end{aligned}$$

□

An important example of Proposition 3.7 is the Pareto case.

Example 3.8. [Pareto distributed severities]
Consider a multivariate SCP model with completely dependent cells and Pareto distributed severities as in Example 2.14. Then we obtain for the c_i

$$\lim_{x\to\infty} \frac{\overline{F}_i(x)}{\overline{F}_1(x)} = \left(\frac{\theta_i}{\theta_1}\right)^{\alpha}, \quad i = 1, \ldots, b, \quad \text{and} \quad \lim_{x\to\infty} \frac{\overline{F}_i(x)}{\overline{F}_1(x)} = 0\,, \quad i = b+1, \ldots, d\,,$$

for some $1 \leq b \leq d$. This, together with Proposition 3.7 leads to

$$\overline{F}^{+}(z) \sim \left(\sum_{i=1}^{b} \frac{\theta_i}{\theta_1}\right)^{\alpha} \left(1 + \frac{z}{\theta_1}\right)^{-\alpha} \sim \left(\sum_{i=1}^{b} \theta_i\right)^{\alpha} z^{-\alpha}\,, \quad z \to \infty\,.$$

Finally, from (2.9) and (3.11) we obtain total OpVaR as

$$\mathrm{VaR}_t^+(\kappa) \sim \sum_{i=1}^b \mathrm{VaR}_t^i(\kappa) \sim \sum_{i=1}^b \theta_i \left(\frac{\lambda\, t}{1-\kappa}\right)^{1/\alpha}, \qquad \kappa \uparrow 1\,.$$

□

We conclude this session with an example showing that Theorem 3.4 does not hold for any general dominating tail.

Example 3.9. [Weibull severities]
Consider a bivariate SCP model with completely dependent cells and assume that the cells' severities are Weibull distributed according to

$$\overline{F}_1(x) = \exp(-\sqrt{x/2}) \qquad \text{and} \qquad \overline{F}_2(x) = \exp(-\sqrt{x})\,, \quad x > 0\,. \tag{3.13}$$

Note that $\overline{F}_{1,2} \in \mathcal{S} \cap \mathcal{R}_\infty$. Equation (3.13) immediately implies that $\overline{F}_2(x) = o(\overline{F}_1(x))$. We find that $H(x_1) = \frac{3}{2}\, x_1$ implying that $\overline{F}^+ \in \mathcal{S} \cap \mathcal{R}_\infty$, since

$$\overline{F}^+(z) = \exp(-\sqrt{z/3})\,, \quad z > 0\,. \tag{3.14}$$

It is remarkable that in this example the total severity (3.14) is heavier tailed than the stand alone severities (3.13), i.e. $F_{1,2}(x) = o(F^+(x))$ as $x \to \infty$. However, from

$$\mathrm{VaR}_t^1(\kappa) \sim 2\left[\ln\left(\frac{1-\kappa}{\lambda\, t}\right)\right]^2 \quad \text{and} \quad \mathrm{VaR}_t^2(\kappa) \sim \left[\ln\left(\frac{1-\kappa}{\lambda\, t}\right)\right]^2, \qquad \kappa \uparrow 1\,,$$

we find that the stand alone VaRs are of the same order of magnitude:

$$\lim_{\kappa \uparrow 1} \frac{\mathrm{VaR}_t^2(\kappa)}{\mathrm{VaR}_t^1(\kappa)} = \frac{1}{2}\,.$$

Nevertheless, equation (3.11) of Theorem 3.5 still holds,

$$\mathrm{VaR}_t^+(\kappa) \sim 3\left[\ln\left(\frac{1-\kappa}{\lambda\, t}\right)\right]^2 = \mathrm{VaR}_t^1(\kappa) + \mathrm{VaR}_t^2(\kappa)\,, \qquad \kappa \uparrow 1\,.$$

□

3.1.2 Multivariate SCP Model with Independent Cells

Let us now turn to a multivariate SCP model where the cell processes S_i, $i = 1, \ldots, d$, are independent and so never jump together. Therefore, we may write the tail integral of S^+ as

$$\overline{\Pi}^+(z) = \Pi([z,\infty) \times \{0\} \times \cdots \times \{0\}) + \cdots + \Pi(\{0\} \times \cdots \times \{0\} \times [z,\infty))\,, \quad z \geq 0\,.$$

Recall from Example 2.5 that in the case of independence all mass of the Lévy measure Π is concentrated on the axes. Hence,

$$\begin{aligned}
\Pi([z,\infty)\times\{0\}\times\cdots\times\{0\}) &= \Pi([z,\infty)\times[0,\infty)\times\cdots\times[0,\infty)),\\
\Pi(\{0\}\times[z,\infty)\times\cdots\times\{0\}) &= \Pi([0,\infty)\times[z,\infty)\times\cdots\times[0,\infty)),\\
&\vdots\\
\Pi(\{0\}\times\{0\}\times\cdots\times[z,\infty)) &= \Pi([0,\infty)\times[0,\infty)\times\cdots\times[z,\infty)),
\end{aligned}$$

and we obtain

$$\begin{aligned}
\overline{\Pi}^{+}(z) &= \Pi([z,\infty)\times[0,\infty)\times\cdots\times[0,\infty))+\cdots+\Pi([0,\infty)\times\cdots\times[0,\infty)\times[z,\infty))\\
&= \overline{\Pi}_1(z)+\cdots+\overline{\Pi}_d(z)\,. \qquad (3.15)
\end{aligned}$$

Now we are in the position to derive an asymptotic expression for total OpVaR in the case of independent cells.

Theorem 3.10. [OpVaR for the independent SCP model] *Consider a multivariate SCP model with independent cell processes $S_1,\dots,S_d$. Then S^+ defines a one-dimensional SCP model with parameters*

$$\lambda^+=\lambda_1+\cdots+\lambda_d \quad \text{and} \quad \overline{F}^{+}(z)=\frac{1}{\lambda^+}\left[\lambda_1\overline{F}_1(z)+\cdots+\lambda_d\overline{F}_d(z)\right], \quad z\geq 0\,. \qquad (3.16)$$

If $\overline{F}_1\in\mathcal{S}\cap(\mathcal{R}\cup\mathcal{R}_\infty)$ and for all $i=2,\dots,d$ there exist $c_i\in[0,\infty)$ such that

$$\lim_{x\to\infty}\frac{\overline{F}_i(x)}{\overline{F}_1(x)}=c_i\,,$$

then, setting $C_\lambda=\lambda_1+c_2\lambda_2+\cdots+c_d\lambda_d$, total OpVaR can be approximated by

$$\mathrm{VaR}_t^+(\kappa)\sim F_1^{\leftarrow}\left(1-\frac{1-\kappa}{C_\lambda\, t}\right), \qquad \kappa\uparrow 1\,. \qquad (3.17)$$

Proof. From Proposition 3.2 we know that S^+ is a compound Poisson process with parameters λ^+ (here following from (3.15)) and F^+ as in (3.16) from which we conclude

$$\lim_{z\to\infty}\frac{\overline{F}^{+}(z)}{\overline{F}_1(z)} = \frac{1}{\lambda^+}[\lambda_1+c_2\,\lambda_2+\cdots+c_d\,\lambda_d]=\frac{C_\lambda}{\lambda^+}\in(0,\infty)\,,$$

i.e.

$$\overline{F}^{+}(z)\sim\frac{C_\lambda}{\lambda^+}\overline{F}_1(z)\,, \quad z\to\infty\,. \qquad (3.18)$$

In particular, $\overline{F}^{+}\in\mathcal{S}\cap(\mathcal{R}\cup\mathcal{R}_\infty)$ and S^+ defines a one-dimensional SCP model. From (2.7) and (3.18) total OpVaR follows as

$$\mathrm{VaR}_t^+(\kappa)\sim F^{+\leftarrow}\left(1-\frac{1-\kappa}{\lambda^+\, t}\right)\sim F_1^{\leftarrow}\left(1-\frac{1-\kappa}{C_\lambda\, t}\right), \qquad \kappa\uparrow 1\,. \qquad \square$$

Example 3.11. [Multivariate SCP model with independent cells]
(1) Assume that $c_i = 0$ for all $i \geq 2$; i.e. $\overline{F}_i(x) = o(\overline{F}_1(x))$, $i = 2, \ldots, d$. We then have $C_\lambda = \lambda_1$ and it follows from (3.17) that independent total OpVaR asymptotically equals the stand alone OpVaR of the first cell. In contrast to the completely dependent case (confer Proposition 3.7 and Example 3.9), this holds for the class $\mathcal{S} \cap (\mathcal{R} \cup \mathcal{R}_\infty)$ and not only for $F_1 \in \mathcal{R}$.

(2) Consider a multivariate SCP model with independent cells and Pareto distributed severities so that the constants c_i of Theorem 3.10 are given by

$$\lim_{x\to\infty} \frac{\overline{F}_i(x)}{\overline{F}_1(x)} = \left(\frac{\theta_i}{\theta_1}\right)^\alpha, \quad i = 1, \ldots, b, \quad \text{and} \quad \lim_{x\to\infty} \frac{\overline{F}_i(x)}{\overline{F}_1(x)} = 0, \quad i = b+1, \ldots, d,$$

for some $b \geq 1$. Then

$$C_\lambda = \sum_{i=1}^{b} \left(\frac{\theta_i}{\theta_1}\right)^\alpha \lambda_i$$

and the distribution tail $\overline{F}^+$ satisfies

$$\overline{F}^+(z) \quad = \quad \frac{1}{\lambda^+} \sum_{i=1}^{b} \lambda_i \left(1 + \frac{z}{\theta_i}\right)^{-\alpha} \quad \sim \quad \frac{1}{\lambda^+} \sum_{i=1}^{b} \lambda_i \, \theta_i^\alpha \, z^{-\alpha}, \qquad z \to \infty.$$

It follows that

$$\mathrm{VaR}_t^+(\kappa) \sim \left(\frac{t \sum_{i=1}^{b} \lambda_i \, \theta_i^\alpha}{1-\kappa}\right)^{1/\alpha} = \left(\sum_{i=1}^{b} \left(\mathrm{VaR}_t^i(\kappa)\right)^\alpha\right)^{1/\alpha}, \qquad \kappa \uparrow 1,$$

where $\mathrm{VaR}_t^i(\kappa)$ denotes the stand alone OpVaR of cell i according to (2.9). For identical cell frequencies $\lambda := \lambda_1 = \cdots = \lambda_b$ this further simplifies to

$$\mathrm{VaR}_t^+(\kappa) \sim \left(\frac{\lambda \, t}{1-\kappa}\right)^{1/\alpha} \left(\sum_{i=1}^{b} \theta_i^\alpha\right)^{1/\alpha}, \quad \kappa \uparrow 1.$$

□

Example 3.12. [Continuation of Example 3.9]
Consider a bivariate SCP model with independent cells and Weibull distributed severities according to (3.13). Accoding to Theorem 3.10 we have $C_\lambda = \lambda_1$ and independent total OpVar is asymptotically given by

$$\mathrm{VaR}_t^+(\kappa) \sim \mathrm{VaR}_t^1(\kappa) \sim 2 \left[\ln\left(\frac{1-\kappa}{\lambda \, t}\right)\right]^2, \qquad \kappa \uparrow 1.$$

□

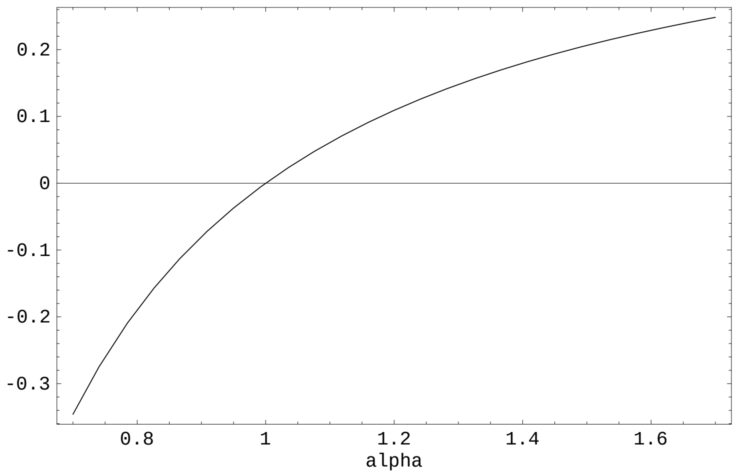

Figure 3.13. *Plot of the relative diversification* $\frac{\mathrm{VaR}_{\|}^{+} - \mathrm{VaR}_{\perp}^{+}}{\mathrm{VaR}_{\|}^{+}} = 1 - 2^{1/\alpha - 1}$ *for two operational risk cells as a function of* α.

Let us now briefly compare the independent Pareto model to the completely dependent Pareto model. A fundamental difference is that, due to the dynamical dependence concept of Lévy copulas, the completely dependent model allows for all cells only identical frequencies, whereas the independent model allows for different cell frequencies. However, if high-severity losses mainly occur in one, say the first cell, both models yield the same asymptotic total OpVaR, namely the stand-alone VaR of the first cell; see Theorem 3.4.

Another interesting case is given when some severity distributions (say b with $2 \leq b \leq d$) are tail equivalent and all others are of lower order. To better compare both models, we now assume the same frequency λ also for the independent model, and denote by $\mathrm{VaR}_{\|}^{+}(\kappa)$ and $\mathrm{VaR}_{\perp}^{+}(\kappa)$ completely dependent total OpVaR and independent total OpVaR, respectively. Then, the following inequality holds as a consequence of convexity ($\alpha > 1$) and concavity ($\alpha < 1$) of the function $x \mapsto x^{\alpha}$:

$$\frac{\mathrm{VaR}_{\perp}^{+}(\kappa)}{\mathrm{VaR}_{\|}^{+}(\kappa)} = \frac{\left(\sum_{i=1}^{b} \theta_i^{\alpha}\right)^{1/\alpha}}{\sum_{i=1}^{b} \theta_i} \quad \begin{cases} < 1\,, & \alpha > 1 \\ = 1\,, & \alpha = 1 \\ > 1\,, & \alpha < 1\,. \end{cases}$$

This result says that for heavy-tailed severity data with $\overline{F}_i(x_i) \sim (x_i/\theta_i)^{-\alpha}$ as $x_i \to \infty$, subadditivity of OpVaR is violated because the sum of stand alone OpVaRs is smaller than independent total OpVaR. This has already been observed in Rootzén and Klüppelberg [13]. For two operational risk cells with $\theta_1 = \theta_2$, the situation is depicted in figure 3.13. Obviously, for very heavy-tailed data with $\alpha < 1$, simple-sum VaR may underestimate the actual total OpVaR up to 30%.

Consider e.g. two cells with constant stand alone OpVar of EUR 100 million, each calculated by a Pareto model with fixed scale parameter $\theta = 1$ and common tail parameter $\alpha = \alpha_1 = \alpha_2$. Table 3.14 compares, for a realistic range of α-values, total OpVaR both for completely dependent and independent data. Obviously, for Pareto risks with $\alpha < 1$, total OpVaR increases superlinearly, when taking on two independent risks, e.g. by opening two new subsidiaries in different parts of the world.

α	$\text{VaR}^+_{\parallel}$	$\text{VaR}^+_{\perp}$
1.2	200.0	178.2
1.1		187.8
1.0		200.0
0.9		216.0
0.8		237.8
0.7		269.2

Table 3.14. *Comparison of total OpVaR for two operational risk cells (each with stand alone VaR of 100 million) in the case of complete dependence* ($\parallel$) *and independence* ($\perp$) *for different values of* α.

3.1.3 Multivariate SCP Models with Arbitrary Dependence Structure

In practice, dependence of different operational risk cells will be somewhere between the two extremes cases discussed so far.

We now present a result that applies to a multivariate SCP model with arbitrary dependence structure. First, we note the following bounds for the tail integral $\overline{\Pi}^+$, which are an geometrically obvious consequence of its definition (3.1). They are well-known for distributional copulas.

Lemma 3.15. [Bounds for Lévy copulas] *Define*

$$\overline{\Pi}^M(z) := \Pi\{x \in [0,\infty)^d : \max(x_1,\ldots,x_d) > z\}\,, \qquad z \geq 0, \tag{3.19}$$

then

$$\overline{\Pi}^M(z) \leq \overline{\Pi}^+(z) \leq \overline{\Pi}^M\Big(\frac{z}{d}\Big)\,, \quad z \geq 0\,. \tag{3.20}$$

In concrete dependence models, this lemma can be easily applied, leading to asymptotic upper and lower bounds for total OpVaR. We show this for the example of a d-dimensional *Clayton Lévy copula*

$$\widehat{C}(u_1,\ldots,u_d) = (u_1^{-\delta}+\cdots+u_d^{-\delta})^{-1/\delta}\,, \quad u_1,\ldots,u_d \in (0,\infty)\,.$$

In Figures 3.18 and 3.19 we show sample paths of two dependent compound Poisson processes, where the dependence is modelled via a Clayton Lévy copula for different parameter values.

Recall that $\lesssim$ means that the quotient of left hand side and right hand side remains bounded above. The formula for $\Lambda_\delta(\cdot)$ is based on Poincaré's inclusion/exclusion formula for measures.

Theorem 3.16. [OpVaR bounds for the Clayton SCP model] *Consider an SCP model with Clayton dependence structure and assume that* $\overline{F}_1 \in \mathcal{S} \cap (\mathcal{R} \cup \mathcal{R}_\infty)$ *and that* $\lim_{z\to\infty} \overline{F}_i(z)/\overline{F}_1(z) = c_i \in [0,\infty)$ *for* $i = 2,\ldots,d$. *Set* $c_1 := 1$ *and* $c := (c_1,\ldots,c_d)$. *Then, total* OpVaR *is for* $\kappa \uparrow 1$ *bounded by*

$$F_1^{\leftarrow}\left(1-\frac{1-\kappa}{\Lambda_\delta(c)\,t}\right) \lesssim \mathrm{VaR}_t^+(\kappa) \lesssim d\,F_1^{\leftarrow}\left(1-\frac{1-\kappa}{\Lambda_\delta(c)\,t}\right)\,, \qquad \kappa\uparrow 1 \tag{3.21}$$

with

$$\begin{aligned}\Lambda_\delta(c) := \lim_{z\to\infty}\frac{\overline{\Pi}^M(z)}{\overline{F}_1(z)} &= \sum_{i=1}^d c_i\lambda_i - \sum_{\substack{i_1,i_2=1\\ i_1<i_2}}^d ((c_{i_1}\lambda_{i_1})^{-\delta}+(c_{i_2}\lambda_{i_2})^{-\delta})^{-1/\delta}\\ &\quad + \sum_{\substack{i_1,i_2,i_3=1\\ i_1<i_2<i_3}}^d ((c_{i_1}\lambda_{i_1})^{-\delta}+(c_{i_2}\lambda_{i_2})^{-\delta}+(c_{i_3}\lambda_{i_3})^{-\delta})^{-1/\delta} \qquad (3.22)\\ &\quad + \cdots + (-1)^{d-1}((c_{i_1}\lambda_{i_1})^{-\delta}+\cdots+(c_{i_d}\lambda_{i_d})^{-\delta})^{-1/\delta}\,.\end{aligned}$$

The following bounds are independent of δ *as* $\kappa\uparrow 1$*:*

$$F_1^{\leftarrow}\left(1-\frac{1-\kappa}{t\,\max(c_1\lambda_1,\ldots,c_d\lambda_d)}\right) \lesssim \mathrm{VaR}_t^+(\kappa) \lesssim d\,F_1^{\leftarrow}\left(\frac{1-\kappa}{t\,(c_1\lambda_1+\cdots+c_d\lambda_d)}\right). \tag{3.23}$$

Proof. Define $\overline{\Pi}^M(\cdot)$ as in (3.19). Now, notice that for any Lévy copula $\widehat{C}$

$$\begin{aligned}\overline{\Pi}^M(z) &= \Pi\{x\in[0,\infty)^d : (x_1>z)\vee\cdots\vee(x_d>z)\}\\ &= \sum_{i=1}^d \overline{\Pi}_i(z) - \sum_{\substack{i_1,i_2=1\\ i_1<i_2}}^d \widehat{C}(\overline{\Pi}_{i_1}(z),\overline{\Pi}_{i_2}(z))\\ &\quad + \sum_{\substack{i_1,i_2,i_3=1\\ i_1<i_2<i_3}}^d \widehat{C}(\overline{\Pi}_{i_1}(z),\overline{\Pi}_{i_2}(z),\overline{\Pi}_{i_3}(z)) \qquad (3.24)\\ &\quad + \cdots + (-1)^{d-1}\widehat{C}(\overline{\Pi}_{i_1}(z),\ldots,\overline{\Pi}_{i_d}(z))\,, \quad z\geq 0\,.\end{aligned}$$

This identity implies for the Clayton Lévy copula relation (3.22). Since $\lim_{z\to 0}\overline{\Pi}_i(z) = \lambda_i$ for all $i = 1,\dots,d$, (3.24) also suggests the notation

$$\overline{\Pi}^M(z) = \Lambda_\delta(1)\,\overline{F}^M(z)\,; \tag{3.25}$$

i.e. $\overline{\Pi}^M(\cdot)$ is the Lévy measure of a compound Poisson process with frequency parameter $\Lambda_\delta(1)$ and severity distribution tail $\overline{F}^M(\cdot)$. Using (3.22) and (3.25) we further obtain

$$\overline{F}^M(z) \sim \frac{\Lambda_\delta(c)}{\Lambda_\delta(1)}\,\overline{F}_1(z)\,, \qquad z\to\infty\,. \tag{3.26}$$

Since F_1 is subexponential, by tail-equivalence, also F^M is. Hence, in the case of an SCP model with Clayton dependence structure, the bounds (3.20) have the following interpretation: the total aggregate loss process S^+ is bounded below and above by univariate SCP models with frequency $\Lambda_\delta(1)$ and severity distributions $\overline{F}^M(z)$ and $\overline{F}^M(\frac{z}{d})$, respectively, whose tail behavior is given by (3.26). Therefore, Theorem 2.13 yields the OpVaR bounds (3.21) and (3.23), where the latter is independent of δ. □

The two bounds (3.23) correspond to the two limiting forms of this copula, one being the completely (positive) dependent, corresponding to $\delta\to\infty$, and the independent model corresponding to $\delta\to 0$.

Example 3.17. [OpVar bounds for the two-dimensional Clayton-Pareto model]
Consider a two-dimensional Clayton SCP model with frequency parameters λ_1,λ_2 and tail equivalent Pareto distributed severities (in case of $\alpha_1\neq\alpha_2$, Theorem 3.4 holds), i.e. for $i=1,2$,

$$\overline{F}_i(x) = \left(1+\frac{x}{\theta_i}\right)^{-\alpha}, \quad x>0, \quad \alpha,\theta_i>0\,.$$

Then,

$$c_2 := \lim_{x\to\infty}\frac{\overline{F}_2(x)}{\overline{F}_1(x)} = \left(\frac{\theta_2}{\theta_1}\right)^{\alpha}$$

and

$$\Lambda_\delta(c_2) = \lambda_1 + \lambda_2\,c_2 - (\lambda_1^{-\delta} + \lambda_2^{-\delta}\,c_2^{-\delta})^{-1/\delta}\,.$$

Hence, δ-dependent OpVaR bound are given by

$$\theta_1\left(\frac{\Lambda_\delta(c_2)\,t}{1-\kappa}\right)^{1/\alpha} \lesssim \mathrm{VaR}_t^+(\kappa) \lesssim 2\,\theta_1\left(\frac{\Lambda_\delta(c_2)\,t}{1-\kappa}\right)^{1/\alpha}, \qquad \kappa\uparrow 1\,. \tag{3.27}$$

For some special parameters we can explicitly calculate total OpVaR, which then can be compared to (3.27). In the following, we refer to Bregman and Klüppelberg [5], Example 3.8. Suppose $\overline{F}_1(x) = \overline{F}_2(x) = (1+x/\theta)^{-\alpha}$ for $x\geq 0$, i.e. $\theta := \theta_1 = \theta_2$, and

$\lambda := \lambda_1 = \lambda_2$. Moreover, assume that the Clayton parameter δ is linked to the severity tail parameter α by $\alpha\,\delta = 1$. Then, on the one hand, using (3.27) with $c_2 = 1$ and $\Lambda_\delta(1) = \lambda\left(2 - 2^{-1/\delta}\right)$, total OpVaR is bounded by

$$\mathrm{VaR}^+_{t,\mathrm{Bound}}(\kappa) \lesssim \mathrm{VaR}^+_t(\kappa) \lesssim 2\,\mathrm{VaR}^+_{t,\mathrm{Bound}}(\kappa)\,, \qquad \kappa \uparrow 1\,. \tag{3.28}$$

with

$$\mathrm{VaR}^+_{t,\mathrm{Bound}}(\kappa) := \theta\left(\frac{\lambda\,t\left(2 - 2^{-\alpha}\right)}{1-\kappa}\right)^{1/\alpha}.$$

On the other hand, according to Bregman and Klüppelberg [5], Example 3.8, we have that

$$\overline{\Pi}^+(z) \sim \lambda\,(\alpha+1)\overline{F}_1(z)\,, \qquad z \to \infty\,,$$

and with our result of Example 2.14, it follows that total OpVaR is given by

$$\mathrm{VaR}^+_t(\kappa) \sim \theta\left(\frac{\lambda\,t\,(\alpha+1)}{1-\kappa}\right)^{1/\alpha}, \qquad \kappa \uparrow 1\,.$$

The ratio

$$\frac{\mathrm{VaR}^+_{t,\mathrm{Bound}}(\kappa)}{\mathrm{VaR}^+_t(\kappa)} \sim \left(\frac{2 - 2^{-\alpha}}{\alpha+1}\right)^{1/\alpha}, \qquad \kappa \uparrow 1\,,$$

which equals 0.75 for $\alpha = 1$, indicates how wide the bounds in (3.28) are.

□

Acknowledgement and Disclaimer

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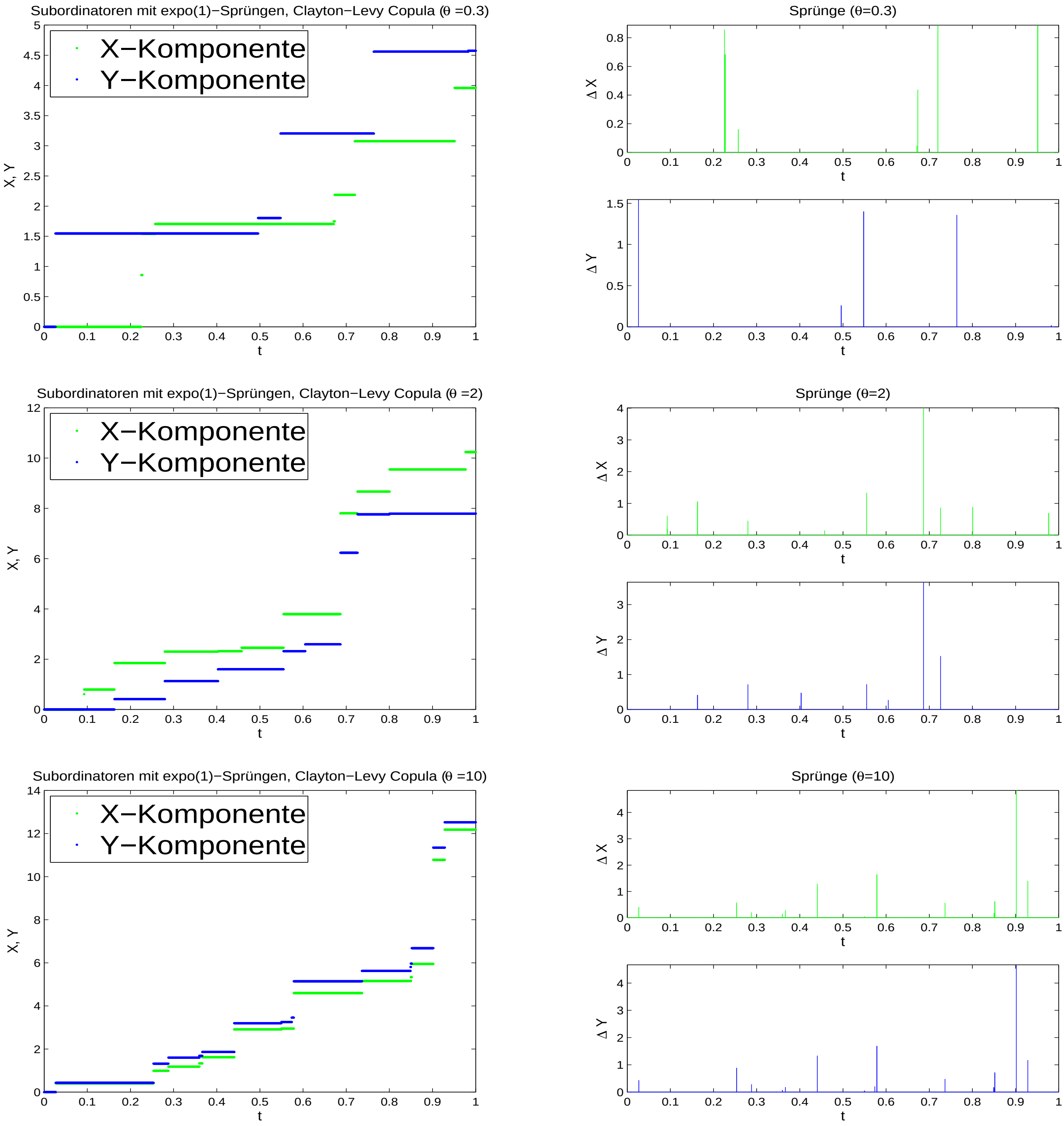

Figure 3.18. *Two-dimensional LDA Clayton-exponential model for different parameter values.* Left column: *compound processes,* right column: *frequencies and severities.* Upper row: $\delta = 0.3$ *(low dependence),* middle row: $\delta = 2$ *(medium dependence),* lower row: $\delta = 10$ *(high dependence).*

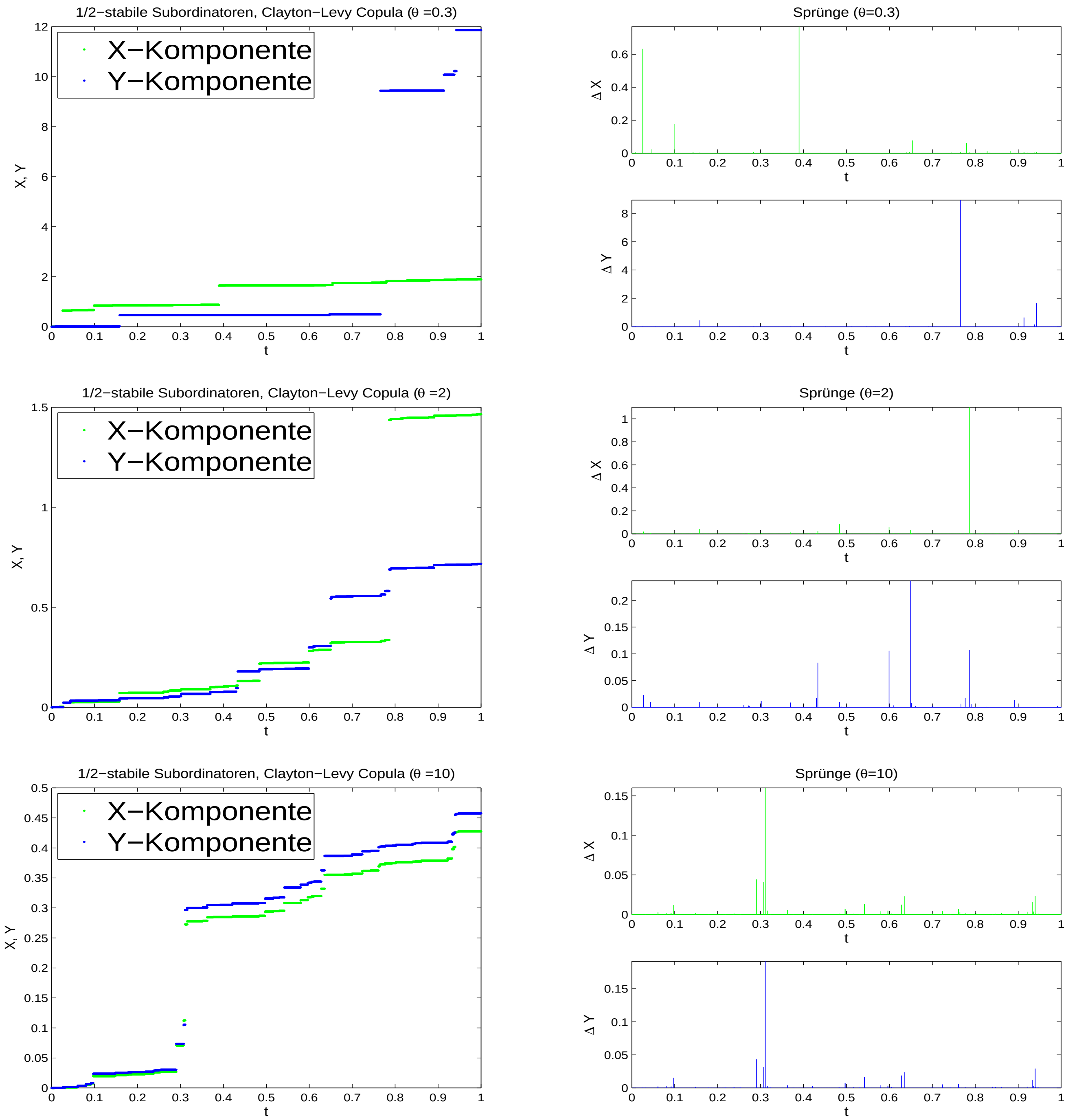

Figure 3.19. *Two-dimensional LDA Clayton-1/2-stable model (severity distribution belongs to $\mathcal{R}_{-1/2}$) for different parameter values.* Left column: *compound processes,* right column: *frequencies and severities.*
Upper row: $\delta = 0.3$ *(low dependence),* middle row: $\delta = 2$ *(medium dependence),* lower row: $\delta = 10$ *(high dependence).*

NC STATE UNIVERSITY

ENTERPRISE RISK MANAGEMENT INITIATIVE

The Information Conveyed in Hiring Announcements of Senior Executives Overseeing Enterprise-Wide Risk Management Processes

Mark Beasley, Don Pagach, Richard Warr

North Carolina State University

What led to this research?

1. **Growing embrace of ERM**

RISE OF THE **CHIEF RISK OFFICER.**

Financial Director, May 1, 2002

"With the increasing importance of risk management, more and more corporates are appointing chief risk officers to provide a holistic approach to risk exposure and put in place an early warning system.

US financial services institutions led the way in the mid-1990s and today there are 200 companies around the world with a board-level chief risk officer (CRO) - and not only in financial services."

Need for Research

1. **In general about Enterprise Risk Management**

   Who is implementing ERM?

   How is it being implemented?

   Why is it being implemented?

2. **In particular – do shareholders/stakeholders value ERM adoption?**

   ERM ultimately should preserve and enhance entity value

Tension

1. ***On one hand***

   Better management of risk should be perceived favorably by shareholders

2. ***On the other hand***

   Portfolio theory suggests that shareholders manage their own risks through diversification

   Thus – not sure if ERM adoption is favorably perceived by shareholders

Background

Stulz (1996, 2003) lays out these arguments

1. **Primary goal of ERM – "By managing risk, a firm can reduce the probability of large adverse cash flow shortfalls."**
2. **Benefits of RM may not be same across all entities – hedging a FC receivable is cheaper than hedging exchange rate risk related to future sales**
3. **An increase in total risk is costly because it is more likely that a firm would have a cash shortfall that would force it to give up valuable projects**
4. **Value creation comes about when ERM reduces *"costly lower tail outcomes"***

General Expectation

Shareholders will perceive benefits to ERM when companies are in situations in which the likelihood of "costly lower tail outcomes" increases

Methodology for Research

Examine the security market to public announcements of the appointment of Chief Risk Officers

Time Period 1992 -2003

Event Period is day of announcement and next day

Sample

Use CRO announcements as proxy for ERM Implementation - CRO suggests top-down, enterprise view

TIME PERIOD 1992-2003:	
# of unique announcements	348
-private firms	<100>
-foreign firms	<36>
-unavailable price data	<52>
-unavailable F/S data	<40>
Final sample	120

Table 1. Sample Statistics for Industry and Year

Year of Announce	Financial	Insurance	Energy	Miscellaneous	Totals
1992	5	0	0	3	8
1993	2	0	1	4	7
1994	1	1	1	3	6
1995	3	1	2	4	10
1996	4	2	3	2	11
1997	3	0	2	0	5
1998	3	1	1	3	8
1999	3	2	1	3	9
2000	2	2	2	5	10
2001	10	1	5	3	19
2002	3	3	3	3	12
2003	8	2	3	2	15
TOTALS	**47**	**15**	**24**	**34**	**120**

Market Reaction to the CRO Appointment Announcement

- **Average CAR = -.001 (not significant)**
- **Suggests no broad consensus as to the benefit/cost of the initiation of an ERM program.**
- **However, the benefits/costs may be firm specific.**

Hypotheses # 1

Hypothesis	Relation to CAR
Growth Options	**positive**

Companies with a greater growth options require more consistent capital investment – – when hedging is cheap a small cost ensures the company will be able to implement all of its projects. Companies with growth options will benefit from implementing ERM.

Hypotheses # 2

Hypothesis	Relation to CAR
Intangible Assets	positive

In times of financial distress intangible assets are likely to be undervalued, in addition, there may not be financial hedges for many intangibles. Companies with large amounts of intangibles will benefit from implementing ERM.

Hypotheses # 3

Hypothesis	**Relation to CAR**
Slack on Balance Sheet (cash ratio)	**negative**

If a company has a large amount of liquid assets it is able to "self-insure" against the probability of large adverse cash flows, these companies will not benefit from implementing ERM.

Hypotheses # 4

Hypothesis	**Relation to CAR**
Earnings Volatility	**positive**

Earnings volatility leads to costs such as missing earnings targets, violating debt covenants, poor relationships with stakeholders – ERM that reduces volatility should increase firm value.

Hypotheses #5

Hypothesis	Relation to CAR
Leverage	**positive**

Greater leverage increases financial risk which increases the cost of capital and borrowing costs. ERM that reduces operational volatility may lead to lower financing costs and should be viewed positively by shareholders.

Hypotheses #6

Hypothesis	**Relation to CAR**
Firm Size	**positive**

Past research (Culp and Miller, 1995) has shown that large firms use hedging to a greater degree this might suggest that these companies have more operational risks. Companies with large amounts of operational risks will benefit from implementing ERM.

Regression Results- full sample

Variable	Predicted Sign	Parameter Estimate	White T-Stat
Intercept		-0.0223	-1.48
Market/Book	+	0.0003	0.52
Intangibles	+	0.0246	0.92
Cash Ratio	**-**	**-0.0395**	**-4.74*****
EPS Vol	+	-0.0000	-0.64
Leverage	+	0.0000	0.00
Size	+	0.0028	1.87*

Multivariate Results

		Financial Firms sub sample		Non-Financial firms sub sample	
Variable	**Sign**	**Parameter Estimate**	**T-Stat**	**Parameter Estimate**	**T-Stat**
Intercept		**-0.006**	**-0.20**	**-0.0327**	**-1.92***
Mkt/Book	+	**0.0023**	**1.49**	**-0.0006**	**-1.22**
Intangibles	+	**0.0670**	**0.56**	**0.0317**	**1.48**
Cash Ratio	-	***-0.0499***	***-2.49*****	***-0.0405***	***-4.49******
EPS Vol	+	**-0.0000**	**0.10**	***0.0004***	***3.42******
Leverage	+	**0.0004**	**1.32**	***-0.0039***	***-3.84******
Size	+	**0.0006**	**0.25**	***0.0048***	***2.59******

Results

- Significant positive relationship for size and earnings volatility
- Significant negative relationship cash ratio
- No results for growth, intangibles
- Leverage – opposite our expectations

What are we missing – future research

Managerial Wealth and Compensation

While shareholders can diversify away firm-specific risks, this is not true of managers.

Manager’s human capital is undiversified

If substantial equity based compensation then managers wealth is (purposefully) undiversified

- The decision to adopt ERM could be motivated by managers own interests and not those of shareholders

Contributions

- Shareholder perceived value of ERM depends on firm-specific characteristics
- Perceived benefit for **non-financial** institutions that
  - Have volatile earnings
  - Have less cash for "self-insurance"
  - Have little leverage

NC STATE UNIVERSITY

ERM ENTERPRISE RISK MANAGEMENT INITIATIVE

Thank you

To learn more about ERM research: **www.erm.ncsu.edu**

Information Conveyed in Hiring Announcements of Senior Executives Overseeing Enterprise-Wide Risk Management Processes

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Information Conveyed in Hiring Announcements of Senior Executives Overseeing Enterprise-Wide Risk Management Processes

ABSTRACT

Enterprise risk management (ERM) is the process of analyzing the portfolio of risks facing the enterprise to ensure that the combined effect of such risks is within an acceptable tolerance. While ERM adoption is on the rise, little academic research exists about the costs and benefits of ERM. Proponents of ERM claim that ERM is designed to enhance shareholder value; however, portfolio theory suggests that costly ERM implementation would be unwelcome by shareholders who can use less costly diversification to eliminate idiosyncratic risk. This study examines equity market reactions to announcements of appointments of senior executive officers overseeing the enterprise's risk management processes. Based on a sample of 120 announcements from 1992-2003, we find that the univariate average two-day market response is not significant, suggesting that a broad definitive statement about the benefit or cost of implementing ERM is not possible. However, our multivariate analysis reveals that market responses to such appointments are significantly positively associated with a firm's size and prior earnings volatility, and negatively associated with the amount of cash on hand relative to liabilities and leverage on the balance sheet. These results are confined to non-financial firms, possibly be due to the regulatory requirements for enterprise risk management that already exist for financial firms. We conclude that the costs and benefits of ERM are firm-specific.

Subject Areas: Enterprise risk management, chief risk officers (CROs), value creation

1. INTRODUCTION

There has been a dramatic change in the role of risk management in corporations (Nocco and Stulz, 2006). Recent corporate financial reporting scandals and evolving corporate governance requirements are increasing the expectation that boards of directors and senior executives effectively manage the risks facing their companies (Kleffner et. al., 2003; Walker et. al., 2002, Walker 2003). To meet these expectations, an increasing number of enterprises are embracing an enterprise-wide risk management approach, often referred to as enterprise risk management or “ERM.”

ERM differs from traditional risk management, where organizations manage individual risks on an isolated basis and where risk interactions are not considered on an enterprise level (Aabo et. al., 2005). Instead, ERM requires an enterprise-wide, top-down approach of managing risks holistically across the enterprise (Kleffner et. al., 2003). In theory, ERM is designed to increase the board’s and senior management’s ability to oversee the portfolio of risks facing an enterprise to ensure that the entity’s risk profile is within the stakeholders’ risk tolerances (Beasley et. al., 2005). The overall purpose of ERM is to protect and enhance shareholder value (COSO, 2004).

While there has been significant growth in the number of ERM programs, little empirical research has been conducted on the value of such programs (Tufano, 1996; Colquitt et al., 1999; Liebenberg and Hoyt, 2003; Beasley et. al., 2005). In particular, there have been few challenges to the view that ERM provides a significant opportunity for competitive advantage (Stroh, 2005) and that ERM is designed to protect and enhance shareholder value. However, modern portfolio theory suggests that an ERM approach to risk management could be value destroying, as shareholders, through portfolio diversification, can eliminate idiosyncratic risk in a virtually costless manner. According to this view, expending corporate resources to reduce idiosyncratic risk will result in a reduction in firm value and shareholder wealth. However, there are circumstances, driven by market imperfections and agency issues, under which risk management may have a positive net present value (Stulz, 1996, 2003), and therefore the true effect of ERM on shareholder value is uncertain.

This study provides empirical evidence on the equity market response to the firm's announcement of the appointment of a senior executive overseeing risk management for the enterprise. This senior executive is often referred to as the chief risk officer or "CRO". Because firms tend not to publicly announce the formation or existence of an ERM process or focus, prior research (see Liebenberg and Hoyt, 2003) and our paper uses first-time CRO announcements as a proxy for ERM implementation.

Using a sample of 120 firms announcing the appointment of a senior executive overseeing the enterprise's risk management processes from 1992-2003, we find that the univariate average two-day market response is not significant, suggesting that a broad statement about the benefit or cost of implementing ERM is not possible. However, our multivariate analysis finds significant relations between the magnitude of equity market returns and certain firm specific characteristics. For the non-financial firms in our sample, announcement period returns are positively associated with firm size and the volatility of prior periods' reported earnings and negatively associated with cash on hand relative to liabilities and leverage. These associations are consistent with ERM adding value for firms in which agency costs or market imperfections are likely to amplify idiosyncratic risks. For financial firms, however, there is no statistical association for financial institutions, likely due to regulatory and rating agency demands for ERM for financial institutions (Basel, 2003; Standard & Poor's, 2005). Our results indicate that the benefits of ERM are not equal across firms, but are dependent on certain firm-specific characteristics.

The paper proceeds as follows: section 2 provides background about the evolution of ERM and develops our hypotheses, section 3 describes the data and methodology, section 4 presents the results, and section 5 concludes and suggests areas for future research.

2. BACKGROUND AND HYPOTHESES DEVELOPMENT

The rapid emergence of ERM is being driven by pressure from a range of sources. For example, the New York Stock Exchange's final corporate governance rules now require audit committees to "discuss guidelines and policies to govern the process by which risk assessment and management is undertaken" (NYSE, 2004). Section 409 of the Sarbanes Oxley Act of 2002 requires public companies to disclose to the public "on a rapid and current basis such additional information concerning material changes in the financial condition or operations of the issuer, in plain English, which may include trend and qualitative information" (SOX, 2002). In addition, emerging regulatory requirements, known as Basel II, expand risk management requirements for financial institutions to include oversight of operational risks in addition to credit and market risks as part of their capital adequacy determinations (Basel, 2003). In response to these requirements, financial institutions are embracing ERM to manage risks across the entity. Rating agencies, such as Standard and Poor's and Moody's, are also examining how managers are controlling and tracking the risks facing their enterprises (Samanta et al., 2005; Standard &

Poor's, 2005). These rating agencies have publicly reported their explicit focus on ERM activities in the financial services, insurance, and energy industries.

One of the challenges associated with ERM implementation is determining the appropriate leadership structure to manage the identification, assessment, measurement, and response to all types of risks that arise across the enterprise. For ERM to be successful, it is critical that the whole organization understand why ERM creates value (Necco and Stulz, 2006). There is a prevailing view that an ERM initiative cannot succeed, because of its scope and impact, without strong support in the organization at the senior management level with direct reporting to the chief executive officer or chief financial officer (Walker, et. al. 2002). Without senior management leadership of the entity-wide risk management processes, cultural differences in risk management assessments and responses across business units lead to inconsistencies in risk management practices across the enterprise (COSO, 2004). Senior executive leadership over ERM helps communicate and integrate the entity's risk philosophy and strategy towards risk management consistently throughout the enterprise.

To respond to this challenge, many organizations are appointing a member of the senior executive team, often referred to as the chief risk officer or CRO, to oversee the enterprise's risk management process (The Economist Intelligence Unit, 2005). Indeed, some argue that the appointment of a chief risk officer is being used to signal both internally and externally that senior management and the board is serious about integrating all of its risk management activities under a more powerful senior-level executive (Lam, 2001). In fact, rating agencies, such as Standard and Poor's, explicitly evaluate organizational structure and authority of the risk management function as part of their assessment of strength and independence of the risk management function (Standard & Poor's, 2005).

Recent empirical research documents that the presence of a CRO is associated with a greater stage of ERM deployment within an enterprise, suggesting that the appointment of senior executive leadership affects the extent to which ERM is embraced within an enterprise (Beasley et. al., 2005). Despite the growth in the appointment of senior risk executives, little is known about factors that affect an organization's decision to appoint a CRO or equivalent, and whether these appointments create value.

Evidence from previous research examining a small sample of firms (n = 26) appointing chief risk officers and a matched control sample finds that firms with greater financial leverage are more likely to appoint a CRO (Liebenberg and Hoyt, 2003). This finding is argued to be consistent with the hypothesis that firms appoint CROs to reduce information asymmetry regarding the firm's current and expected risk profile, thus suggesting shareholders should value CRO appointments.

This study extends the work of Liebenberg and Hoyt (2003) by examining the equity market response to the firm's announcement of the hiring of a senior executive overseeing risk management. To our knowledge, previous research has not investigated explanations for the observed cross-sectional differences in the magnitude of the stock price response to the CRO hiring announcement. Because corporations disclose only minimal details of their risk management programs (Tufano, 1996), our focus on hiring announcements of senior risk officers attempts to measure the valuation impact of the firm's signaling of an enterprise risk management process.

The basic premise that ERM is a value creating activity actually runs counter to modern portfolio theory. Portfolio theory shows that under certain assumptions, investors can fully diversify away all firm (or idiosyncratic) risk (Markowitz, 1952).[1] This can usually be achieved costlessly by randomly adding stocks to an investment portfolio. Because investors can diversify away firm-specific risk, they should not be compensated for bearing such risk (for example, risks associated with holding an undiversified portfolio). As a result, investors should not value costly attempts by firms to reduce firm-specific risk, given an investor's costless ability to eliminate this type of risk. Thus, under modern portfolio theory, any expenditure on risk management is value destroying and should be negatively perceived by investors.

While portfolio theory might suggest a lack of value associated with ERM implementation, markets do not always operate in the manner presented by Markowitz (1952). Stulz (1996, 2003) presents arguments under which risk management activities could be value increasing for shareholders in the presence of agency costs and market imperfections. The motivation behind Stulz's work is to reconcile the apparent conflict between current wide-spread corporate embrace of risk management practices and modern portfolio theory.

Stulz (1996, 2003) argues that any potential value creation role for risk management is in the reduction or elimination of "costly lower-tail outcomes." Lower tail outcomes are those events in which a decline in earnings or a large loss would result in severe negative consequences for the firm. Thus, when a firm is faced with the likelihood

[1] See Markowitz (1952) although the number of papers that have extended this early seminal work is extensive.

of lower tail outcomes, engaging in risk management that reduces the likelihood of real costs associated with such outcomes could represent a positive net present value project. Only firms facing an increased likelihood of these actual negative consequences associated with lower tail events will benefit from risk management, while other firms not facing such events will see no benefit at all (Stulz, 1996, 2003), and indeed could be destroying value by engaging in costly risk management.

Costs associated with lower tail events can be significant, calling for greater risk management activities as the likelihood of such occurrences increases. Events such as bankruptcy and financial distress involve direct cost outlays such as payments to lawyers and courts. These events involve indirect costs as well, such as an inability to pursue strategic projects, loss of customer confidence, and inability to realize the full value of intangible assets. Costs to shareholders can also include a decline in debt ratings and the higher borrowing costs that result. Shareholders may also bear indirect costs associated with the impact of lower tail outcomes on other stakeholders. For example, managers and key employees of public firms have an undiversifiable stake in the firm, and will bear a greater proportion of the cost of a lower tail event. Assuming an efficient labor market, employees will demand higher compensation for their risk bearing, and this higher compensation cost will result in lower cash flows to equity holders.[2] Other stakeholders may be adversely affected by financial distress – for example, suppliers may be reluctant to enter into long term contracts with the firm if the potential for future payment is uncertain, and higher supplier costs will hurt shareholder value. As the likelihood of these

[2] Although we do not specifically address managerial characteristics in our tests, we discuss their potential impact in section 5.

occurrences increases, the potential benefit from enterprise risk management increases also.

We assume that the hiring of a chief risk officer implies that the firm is implementing an ERM program and will expend some effort, and more importantly, corporate resources, on methods of reducing the likelihood of these lower-tailed events. The idea that ERM is not costless is important to out study. A costless ERM program that reduces earnings variability but not the mean level of earnings is likely to be viewed by shareholders as harmless at worse and perhaps beneficial. A costly ERM program may actually be harmful if the value benefits of the risk reductions do not offset the costs of securing the risk reductions.

The assumption that CRO appointments signal adoption of ERM is fundamental to prior studies and to our study, and it is worth exploring the reasons why a firm might appoint a CRO. First, the appointment may by due to the position being created for the first time, and in this case it would seem reasonable to assume that the firm has started paying more attention to ERM. Second, it could be that the CRO appointment is a replacement of an existing CRO. In this case it is not clear whether ERM adoption has already taken place or is currently underway. Finally, a CRO appointment may be little more than a title change that more accurately reflects a manager’s responsibility, where the manager has already been heavily engaged in ERM. Out of these three possibilities, it is only the first that could reasonably be relied upon as a signal of first time ERM adoption. To the extent that CRO appointments may be due to all three of these reasons, tests that use CRO appointments will be biased towards the null of finding no effect because of the noise introduced by the second and third reasons.

Our study of equity market responses to announcements of appointments of CROs builds upon Stulz (1996, 2003) to examine firm-specific variables that reflect the firm's likelihood of experiencing a lower-tailed event. These variables reflect firm-specific factors that finance theory suggests should explain the value effects of corporate risk management. These variables are described more fully below, and include several factors that may impact earnings volatility such as the extent of the firm's growth options, intangible assets, cash reserves, earnings volatility, leverage, and firm size.

While the focus of our paper is on firm characteristics and their influence on the market reaction to ERM adoption, we have specifically not included managerial characteristics in our analysis. The effect of managerial characteristics is a potentially very interesting area of future research, but beyond the scope of the current paper. We discuss the potential impact of managerial characteristics in section 5 of the paper.

***Growth Options*.** Firms with extensive growth options require consistent capital investment and may face greater asymmetric information regarding their future earnings (Myers, 1984; Myers and Majluf, 1984). When in financial distress, growth options are likely to be undervalued and that distress may lead to underinvestment in profitable growth opportunities. When growth firms have limited access to financial markets, they may face higher costs in raising external capital, perhaps due to the asymmetric information surrounding these growth options, in a period of time when steadier streams of cash flows are desired (see Froot, Scharfstein, and Stein, 1993; Gay and Nam, 1998). We hypothesize that the firms with greater growth options will have a positive abnormal return around hiring announcements of CROs.

Hypothesis 1: *Ceteris paribus, the market reaction to firm announcements of appointments of CROs will be positively associated with the firm's growth options.*

Intangible Assets. Firms that have more opaque assets, such as goodwill, are more likely to benefit from an ERM program because these assets are likely to be undervalued in times of financial distress (Smith and Stulz, 1985). Although this benefit directly accrues to debtholders, stockholders should benefit through lower interest expense charged by the debtholders. Nance, Smith and Smithson (1993), Geczy, Minton and Schrand (1997) and Dolde (1995) find that firms with high levels of research and development expense (often correlated with creation of intangible assets) are more likely to use derivatives to hedge risk. Conversely, Mian (1996) finds no relation between market-to-book (a common proxy for intangibles) and derivative use. We hypothesize that the firms with a large amount of intangible assets will have a positive abnormal return around hiring announcements of CROs:

> ***Hypothesis 2:*** *Ceteris paribus, the market reaction to firm announcements of appointments of CROs will be positively associated with the firm's amount of intangible assets.*

Cash Ratio Firms with greater amounts of cash on hand (as defined as cash/total liabilities) are less likely to benefit from a risk management program, as these firms can protect themselves against a liquidity crisis that might result from some lower tail outcomes. Froot, Scharfstein and Stein (1993) show that a firm's hedging activity can be value creating if it ensures that the firm has sufficient cash flow to invest in positive NPV projects. However, Tufano (1996) argues that cash flow hedging can create agency conflicts if managers are able to pursue projects without the discipline of external capital markets. In addition, less cash on hand can increase the likelihood of financial distress for levered firms (Smith and Stulz, 1985). We hypothesize that firms with greater amounts of cash will have a negative abnormal return around announcements of CRO appointments.

> ***Hypothesis 3:*** *Ceteris paribus, the market reaction to firm announcements of appointments of CROs will be negatively associated with the firm's cash ratio.*

Earnings Volatility. Firms with a history of greater earnings volatility are more likely to benefit from ERM. Firms that have large amounts of earnings volatility have a greater likelihood of seeing a lower tail earnings outcome, missing analysts' earnings forecasts, and violating accounting based debt covenants (Bartov, 1993). In addition, managers may smooth earnings to increase firm's share prices by reducing the potential loss shareholders may suffer when they trade for liquidity reasons (Goel and Thakor, 2003). In an earnings smoothing model, shareholders reduce the price they pay for companies with high earnings volatility. Thus, managers have an incentive to smooth earnings in order to ensure that long-term share price performance is not lower than its true value. We hypothesize that firms experiencing a high variance of earnings per share (EPS) will have a positive abnormal return around hiring announcements of CROs:

> ***Hypothesis 4:*** *Ceteris paribus, the market reaction to firm announcements of appointments of CROs will be positively associated with the firm's variance in earnings per share (EPS).*

Leverage. Greater financial leverage increases the likelihood of financial distress. Under financial distress, firms are likely to face reductions in debt ratings and consequently higher borrowing costs. Furthermore, many of the rating agencies, such as Moody's and Standard & Poor's, incorporate ERM into their rating methodology (Aabo et. al., 2005; Standard & Poor's, 2005). More robust ERM practices may lead to lower financing costs. We hypothesize that the firms with high leverage will have a positive abnormal return around hiring announcements of CROs:

Hypothesis 5: *Ceteris paribus, the market reaction to firm announcements of appointments of CROs will be positively associated with extent of the firm's leverage.*

Size. Research examining the use of financial derivatives finds that large companies make greater use of derivatives than smaller companies. Such findings confirm the experience of risk management practitioners that the corporate use of derivatives requires considerable upfront investment in personnel, training, and computer hardware and software, which might discourage smaller firms from engaging in their use (Stulz, 2003). Furthermore, larger firms have more to lose and are subject to greater political and reputation-related risks. Although Stulz (2003) focuses much of his attention on risk management with derivatives, we make no distinction about the nature of the risk management activities. We hypothesize that larger firms will have a positive abnormal return around hiring announcements of CROs:

Hypothesis 6: *Ceteris paribus, the market reaction to firm announcements of appointments of CROs will be positively associated with firm size.*

4. DATA AND METHOD

Our study method examines the impact of firm-specific characteristics on the equity market response to announcements of appointments of CROs within the enterprise. To obtain a sample of such appointments, we conduct a search of hiring announcements of senior risk management executives made during the period 1992-2003. Announcements are obtained by searching the business library of LEXIS-NEXIS for announcements containing the words “announced”, “named”, or “appointed” in conjunction with position descriptions of “chief risk officer” or “risk management” (consistent with the approach used by Liebenberg and Hoyt (2003)). We searched the period of 1992 through 2003 and identified 348 observations. Each observation is unique to a firm, in that it represents a firm's first announcement during the period searched, subsequent announcements by a firm are excluded. By starting our search in 1992, we hope to capture the initial creation of a CRO position, as the presence of CRO positions became more prevalent in the later 1990s. However, as we discussed earlier, if some of these appointments are merely changes in personnel we will not be capturing unique or initial appointments. Contamination of our data set by these noisy observations will serve to bias our results towards finding no effect of CRO appointments.

From this list of 348 observations, we exclude 100 announcements made by private corporations, given the lack of observable financial and operational data needed to test our hypotheses. We exclude an additional 36 announcements made by foreign companies and 46 firms that did not have the required security market data necessary for our analysis. Finally, 46 observations of public companies are dropped for not having the required financial statement data needed for analysis. The final sample includes 120 observations.

Table 1 provides information about our final sample of 120 observations. The data in Table 1 documents the increase in CRO announcements over time. In addition, the sample is concentrated in three industries, financial services (39.2%), insurance (12.5%) and energy services (20.0%). These industries are often cited as being in the forefront of implementation of enterprise risk management (Beasley et. al., 2005). This industry distribution is consistent with other survey data finding that highly regulated industries, such as financial services and insurance, are among the early adopters of enterprise risk management due to growing regulatory calls for ERM (such as Basel, 2003), while manufacturing companies consistently lag more regulated industry sectors (PwC, 2004).

Fallout from the Enron debacle has placed greater expectations on energy sector firms to embrace enterprise-wide risk management, as evidenced by this industry's subsequent formation of the Committee of Chief Risk Officers (CCRO) focused on developing best practices for ERM in the energy sector. The same three industries are also the focus of rating agencies, such as Standard & Poor's, Moody's, and Fitch that formally evaluate ERM practices of firms in these industries as part of the credit rating process.

[Insert Table 1 About Here]

Table 2 provides descriptive statistics for the sample. The mean (median) market value of equity, assets and sales, in millions of dollars, are $8,242.1 ($3,008.5), $39,002.1 ($7,347.4) and $8,709.0 ($3,032.3), respectively. Firms in our sample are on average quite large, however, there is a large amount of variance in these size metrics. Each of these variables is measured as of the end of the most recent fiscal year prior to the hiring announcement.

[Insert Table 2 About Here]

Table 2 also contains information about the cumulative abnormal return (CAR) for the event period. We measure the announcement period as the day of the hiring announcement plus the following day. The abnormal return is computed using the three factor Fama-French methodology (1993).[3] The announcement period CAR for the entire sample of announcements is -0.001 and is not statistically different from zero. The average CAR indicates that we cannot make a broad definitive statement about the benefit (or cost) of implementing ERM, as on average, there is no value effect; however, there is substantial

[3] Our results are qualitatively unchanged if we use a single factor model to estimate the abnormal returns.

cross sectional variation. For this reason, our study focuses on the cross-sectional firm characteristics that we hypothesize may determine the value of effects of risk management.

We proxy for the hypotheses of interest using the following independent variables:

Market/Book	=	market to book ratio serves as our proxy for growth options and is computed as the market value of the firm divided by its book value of equity, with both variables measured at the end of the fiscal year prior to the announcement.
Intangibles	=	book value of intangible assets divided by total assets measured at the end of the fiscal year prior to the announcement.
Cash Ratio	=	the amount of cash as reported at the end of the fiscal year-end prior to the announcement divided by total liabilities measured at the end of the fiscal year prior to the announcement.
EPS Vol	=	standard deviation of the change in earnings per share over the eight quarters prior to the announcement.
Leverage	=	total liabilities divided by market value of equity measured at the end of the fiscal year prior to the announcement.
Size	=	the natural logarithm of the firm's market value of equity as measured at the end of the most recent fiscal quarter prior to the announcement.

Due to the large number of financial service firms in our sample we disaggregate our sample into financial service industry firms and non-financial service industry firms. Descriptive information about these two sub-samples is reported in Table 3. The sample of financial service firms is significantly larger in terms of assets and is, not surprisingly, more highly leveraged than the non-financial service firms. Finally, the financial service firms have, on average, reported fewer intangibles as a percentage of total assets and have less variable earnings per share than the sample of non-financial service firms.

[Insert Table 3 About Here]

Table 4 presents correlations of our main variables. We observe a significant negative correlation between the cash ratio and the announcement return, CAR. This relation is consistent with our hypothesis that the market will view ERM for firms that can buffer risky outcomes with cash as wealth destroying. We also observe a positive relation between Size and CAR, suggesting the ERM implementation is valued more at larger firms. A few other correlations are worth noting. First, the positive correlation between EPS Vol and Market to book value is consistent with high growth firms being more risky. EPS Vol is also greater for firms with more leverage. The negative relation between Intangibles and Leverage is consistent with debt frequently being secured against tangible assets. In general these correlations conform to our expectations.

[Insert Table 4 About Here]

To examine whether there are cross sectional differences in our hypothesized associations between firm-specific characteristics and the equity market reaction to announcements of appointments CROs, we use multivariate regression analysis. Specifically, the general form of the model is the following (firm subscripts are omitted):

$$CAR(0,+1) = a_0 + a_1 Market/Book + a_2 Intangibles + a_3 Cash\ Ratio + a_4 EPS\ Vol + a_5 Leverage + a_6 Size + e \quad (1)$$

We expect to observe a positive association between the event period abnormal return and the market to book value ratio, the level of intangible (“opaque”) assets, earnings volatility, leverage, and firm size. We expect to observe a negative association between the event period abnormal return and the firms' cash ratio. The next section presents the results of our multivariate regression analysis as defined by equation (1).

4. RESULTS

Table 5 presents the results based on multivariate regression analysis where the dependent variable represents the cumulative abnormal return for the announcement period regressed on our six variables of interest for the full sample of 120 observations. The F-Value of model is 3.47, which is significant at the 0.004 level and the Adjusted R^2 is 0.111.

[Insert Table 5 about here]

Consistent with our second hypothesis, we find a significantly negative relationship between the event period cumulative abnormal return and the cash ratio. The primary inference from the regression results is that investors view negatively the implementation of ERM programs for firms with large amounts of cash on hand. This result is consistent with financial theory that suggests firms that have large cash reserves are less likely to suffer financial distress and thus have less need to manage risks related to future financial problems. Thus, our results support Hypothesis 2.

In contrast, we do not observe statistically significant associations between the event period cumulative abnormal return and our measures for Market to book, Intangibles, EPS Vol and Leverage. These results suggest that the extent of growth opportunities, holdings of intangible assets, recent earnings volatility and capital structure do not impact the information content of senior executive hiring announcements. Thus, Hypotheses 1, 3, 4 and 5 are not supported by our full sample.

We find a positive association between the event period cumulative abnormal return and the firm’s Size. This finding is consistent with our expectation as stated in Hypothesis 6 that larger firms are more likely to benefit from risk management activities than smaller firms.

As indicated by Table 1, a large portion (39.1%) of our sample is in the financial services industries. Due to the nature of risks facing financial services firms, such as credit and market risks, such institutions have incorporated risk management practices as part of their day-to-day management processes. Regulatory expectations that financial services firms effectively manage credit and market risk have been in place for decades. In recent years, there have been greater calls for financial institutions to expand their risk oversight activities to include broader categories of risks threatening operations (Basel, 2003; Bies, 2004; Samanta et al., 2005). New regulations issued by the Bank of International Settlements, a global association of banking regulators, require that financial services firms adopt broader enterprise wide risk management processes to determine capital reserve requirements (Basel, 2003). Additionally, many of the rating agencies, such as Moody's and Standard & Poor's, first launched their programs for incorporating information about ERM practices in their overall rating assessments by first focusing on entities in the financial services industry (Standard & Poor's, 2005). As a result, regulatory expectations for ERM in financial services institutions may render our six hypotheses for ERM value irrelevant.

To examine whether the predicted associations described by our hypotheses are supported for firms in the financial services firms, we conducted our same multivariate regression analysis for the sub-set of firms (n = 47) that are in the financial services industry. We also conducted the same analysis for the remaining subset of firms not in the financial services industry (n = 73). The results of this analysis are reported separately in Table 6.

[Insert Table 6 about here]

We find that of the six independent variables only the cash ratio variable is found to be significantly associated with the market reaction to announcements of appointments of CROs for the financial services firms in our sample, with the overall model not significant (F-Value of 1.04, $p = 0.413$). This result is consistent with the belief that regulatory pressures and requirements drive financial services institutions to embrace enterprise-wide risk management processes, not firm-specific financial characteristics.

In contrast, the results shown in Table 6 for the sub-sample of firms in industries other than financial services indicate that, in the absence of regulatory expectations, several of the firm's financial characteristics may explain the firm's value enhancement due to ERM adoption. Our overall model is significant ($p = 0.001$), with an F-Value of 5.66 and R^2 of 0.279.

For our non-financial firms ($n = 73$), we find that announcement period market returns are positively associated with the firm's prior earnings volatility and size, while negatively associated with the extent of cash on hand and leverage. There is no statistical association between the announcement period returns and the firm's growth or extent of intangible assets.

While the results for earnings volatility, size and cash on hand are consistent with our expectations, the findings for leverage are opposite our expectations. One explanation for this result is that shareholders of highly leveraged firms may not want risk reduction as it reduces the value of the option written to them by debtholders. In this case, the option value outweighs the dead weight costs of bankruptcy that are increased with high leverage. Our finding is consistent with Hoyt and Liebenberg (2006) who find the extent of ERM usage is negatively associated with the extent of leverage.

The results for our two sub-samples suggest that results for the full sample of announcement firms examined in Table 5 are driven mostly by the non-financial services firms, suggesting that key financial characteristics drive stockholder value of ERM related processes for firms outside financial services, while regulatory or other demands for risk management affect those processes in the financial services sector.

5. CONCLUSION AND LIMITATIONS

This study provides evidence on how the perceived value of enterprise risk management processes varies across companies. While ERM practices are being widely embraced within the corporate sector, not all organizations are embracing those practices and little academic research exists about the benefits and costs of ERM. Overall, we find no aggregate significant market reaction to the hiring of CROs for either the financial service or non-financial service firms. This result suggests that we cannot make any broad claims about ERM benefits or costs to shareholders across a wide range of firms.

The absence of an overall average market reaction does not mean that the market is not reacting. In cross section analysis, we find that a firm's shareholders respond largely in accordance with our expectations and value ERM where the program can enhance value by overcoming market distortions or agency costs. Specifically, we find that shareholders of large firms that have little cash on hand value ERM. Furthermore, shareholders of large non-financial firms, with volatile earnings, low amounts of leverage and low amounts of cash on hand also react favorably to the implementation of ERM. These findings are consistent with the idea that a well implemented ERM program can create value when it reduces the likelihood of costly lower tail outcomes such as financial distress.

Despite providing some insights into the value of ERM adoption, there are limitations to our study. First, while we are able to observe announcements of appointments of senior executives overseeing risk management practices, we are unable to directly observe the extent to which the related firms actually embrace ERM. Further study of more specific announcements about ERM activities is therefore warranted. Second, we are only able to measure short-term reactions to these CRO announcements and cannot provide insight into the long term value of ERM. Third, we only measure equity market reactions and as a result, we do not provide any evidence of ERM's value to other stakeholders, such as creditors, employees, supplies, among others. Fourth, we do not know whether ERM processes lead to greater transparency about risks to stakeholders. For a subset of our sample firms, we reviewed their financial statement disclosures in public filings and saw no increase in risk-related disclosures before and after the CRO announcements. We believe, however, that determination of how ERM impacts risk reporting to stakeholders represents an avenue of future research.

Finally, we have not addressed the issue of managerial characteristics on ERM adoption. Managers hold an undiversified stake in their company as all of their labor capital is tied up in the firm. In addition many managers receive equity based compensation resulting in his/her personal portfolio being over weighted in the firm's stock, and thus undiversified. Managerial preferences for ERM may depend on the manager's compensation. For example; a manager that only receives salary based compensation may favor smoother earnings over a higher stock value, if the latter is associated with more volatility. In this case the manager would favor ERM adoption.

The issue is less clear for managers with stock based compensation or share ownership in the firm. In this case the manager may hold an undiversified portfolio and would favor ERM as a means to reduce his overall portfolio risk. However, for levered firms, equity can be viewed as a call option on the firm's assets, and this option value is increasing in the volatility of the value of the firm's assets. Therefore, the impact of managerial stock ownership is unclear as managers could either favor or eschew ERM. For managers with option grants, the value of these options will be increasing in the volatility of the firm's equity, and managers who seek to increase the value of their options would also avoid ERM. However, if managers view in the money options as equity substitutes, and wish to reduce their portfolio risk, they would favor ERM.

The role of managerial compensation is further complicated by board structure and the endogenous relation between firm characteristics such as leverage, industry and managerial compensation. We therefore leave the subject of ERM adoption and managerial characteristics as an important topic for future research.

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Table 1
Sample Statistics for Industry and Year

Year of Announcement	Financial Industry	Insurance Industry	Energy Industry	Miscellaneous	Totals
1992	5	0	0	3	8
1993	2	0	1	4	7
1994	1	1	1	3	6
1995	3	1	2	4	10
1996	4	2	3	2	11
1997	3	0	2	0	5
1998	3	1	1	3	8
1999	3	2	1	3	9
2000	2	2	2	4	10
2001	10	1	5	3	19
2002	3	3	3	3	12
2003	8	2	3	2	15
TOTAL	**47**	**15**	**24**	**34**	**120**

Table 2
Descriptive Statistics – Full Sample

Variable	N	Mean	Median	Standard Deviation	Minimum	Maximum
Size Metrics:						
Assets	120	39,002.1	7,347.4	82,624.0	18.2	616,064.1
Liabilities	120	35,339.5	5,300.5	78,712.0	0.2	594,494.6
MVE	120	8,242.1	3,008.5	14,609.0	8.0	93,259.6
BVE	120	3,662.7	1,816.3	5,383.0	7.6	33,705.1
Sales	120	8,709.0	3,032.3	19,743.0	19.3	162.558.0
Independent Variable:						
CAR	120	-0.001	-0.002	0.032	-0.100	0.111
Hypothesized Variables of Interest:						
Market/Book	120	2.291	1.824	3.013	0.256	27.540
Intangibles	120	0.058	0.014	0.104	0.000	0.564
Cash Ratio	120	0.136	0.060	0.242	0.001	1.710
EPS Vol	120	9.414	1.421	38.719	0.022	288.35
Leverage	120	6.084	2.197	10.642	0.002	74.867
Size	120	8.765	8.902	2.223	2.901	13.331

Where; Assets = the amount of total assets as reported at the end of the fiscal year-end prior to the announcement, in million of dollars. Liabilities = the amount of total liabilities as reported at the end of the fiscal year-end prior to the announcement, in million of dollars. MVE = the market value of equity at the end of the most recent fiscal quarter prior to the announcement, in million of dollars. BVE = the book value of equity at the end of the fiscal year-end prior to the announcement, in million of dollars. Sales = the amount of sales in the year prior to the announcement, in millions of dollars. CAR = the cumulative abnormal return for the event period, the announcement day plus the following day, computed using the Fama-French three factor model. Market/Book = the market value of the firm divided by its book value of equity reported at the end of the fiscal year-end prior to the announcement. Intangibles = book value of intangible assets divided by total assets reported at the end of the fiscal year-end prior to the announcement. Cash Ratio = the amount of cash as reported at the end of the fiscal year-end prior to the announcement divided by total liabilities. EPSVol = the standard deviation of the change in earnings per share over the eight quarters prior to the announcement. Leverage = total liabilities divided by market value of equity reported at the end of the fiscal year-end prior to the announcement. Size = the natural logarithm of MVE at the end of the fiscal year-end prior to the announcement.

Table 3
Descriptive Statistics - Sub-samples of Financial and Non-Financial Firms

Panel A: Financial Firms

	N	Mean	Median	Standard Deviation	Minimum	Maximum
Size Metrics:						
Assets	47	75,888.6	33,703.8	115,458.0	18.2	616,064.1
Liabilities	47	71,424.3	30.774.8	110.674.0	4.7	594,494.6
MVE	47	10,633.2	3,736.8	15,860.0	10.0	72,847.1
BVE	47	4,464.3	2,166.6	5,357.0	13.5	21,569.5
Sales	47	7,587.7	2,996.2	11,878.0	19.3	66,070.2
Independent Variable:						
CAR	47	0.003	0.001	0.031	-0.052	0.111
Hypothesized Variables of Interest:						
Market/Book	47	2.067	1.806	1.540	0.333	9.295
Intangibles	47	0.023	0.010	0.050	0.000	0.259
Cash Ratio	47	0.163	0.096	0.231	0.007	1.347
EPSVol	47	7.261	0.597	39.515	0.022	272.020
Leverage	47	11.157	6.602	14.178	0.134	74.867
Size	47	9.681	10.425	2.363	2.900	13.331

Continued on next page.

Table 3
Continued.

Panel B: Non-Financial Firms

	N	Mean	Median	Standard Deviation	Minimum	Maximum
Size Metrics:						
Assets	73	15,253.3	4,017.5	36,145.0	29.0	276,229.0
Liabilities	73	12,106.8	3,308.8	31,893.0	0.2	248,692.0
MVE	73	6,702.6	2,137.6	13,634.0	8.0	93,259.6
BVE	73	3,146.5	1,494.92	5,373.0	7.6	33,705.1
Sales	73	9,431.0	3,307.3	23,510.0	22.3	162,558.0
Independent Variable:						
CAR	73	-0.003	-0.003	0.033	-0.100	0.069
Hypothesized Variables of Interest:						
Market/Book	73	2.436	1.852	3.665	0.256	27.540
Intangibles	73	0.080	0.023	0.122	0.000	0.564
Cash Ratio	73	0.119	0.047	0.249	0.001	1.710
EPSVol	73	10.800	1.972	38.409	0.054	288.335
Leverage	73	2.817	1.315	5.582	0.002	37.440
Size	73	8.175	8.298	1.923	3.367	12.529

Where; Assets = the amount of total assets as reported at the end of the fiscal year-end prior to the announcement, in million of dollars. Liabilities = the amount of total liabilities as reported at the end of the fiscal year-end prior to the announcement, in million of dollars. MVE = the market value of equity at the end of the most recent fiscal quarter prior to the announcement, in million of dollars. BVE = the book value of equity at the end of the fiscal year-end prior to the announcement, in million of dollars. Sales = the amount of sales in the year prior to the announcement, in millions of dollars. CAR = the cumulative abnormal return for the event period, the announcement day plus the following day, computed using the Fama-French three factor model. Market/Book = the market value of the firm divided by its book value of equity reported at the end of the fiscal year-end prior to the announcement. Intangibles = book value of intangible assets divided by total assets reported at the end of the fiscal year-end prior to the announcement. Cash Ratio = the amount of cash as reported at the end of the fiscal year-end prior to the announcement divided by total liabilities. EPSVol = the standard deviation of the change in earnings per share over the eight quarters prior to the announcement. Leverage = total liabilities divided by market value of equity reported at the end of the fiscal year-end prior to the announcement. Size = the natural logarithm of MVE at the end of the fiscal year-end prior to the announcement.

Table 4
Pearson Rank Correlations Between Variables

	Market/ Book	Intangibles	Cash Ratio	EPS Vol	Leverage	Size
CAR	0.051 (0.58)	-0.005 (0.96)	-0.339 (0.00)	-0.039 (0.67)	0.019 (0.84)	0.265 (0.00)
Market/Book		0.134 (0.15)	-0.029 (0.75)	0.199 (0.03)	-0.095 (0.30)	0.058 (0.53)
Intangibles			0.147 (0.11)	-0.051 (0.58)	-0.198 (0.030)	-0.230 (<0.01)
Cash Ratio				-0.044 (0.63)	-0.026 (0.78)	-0.270 (<0.01)
EPS Volatility					0.314 (0.00)	-0.115 (0.21)
Leverage						0.178 (0.05)

This table provides univariate correlations between variables used in this study. Two-tailed probability values are in parentheses. The variables are defined as follows: CAR = the cumulative abnormal return for the event period, the announcement day plus the following day, computed using the Fama-French three factor model. Market/Book = the market value of the firm divided by its book value of equity reported at the end of the fiscal year-end prior to the announcement. Intangibles = book value of intangible assets divided by total assets reported at the end of the fiscal year-end prior to the announcement. Cash Ratio = the amount of cash as reported at the end of the fiscal year-end prior to the announcement divided by total liabilities. EPSVol = the standard deviation of the change in earnings per share over the eight quarters prior to the announcement. Leverage = total liabilities divided by market value of equity reported at the end of the fiscal year-end prior to the announcement. Size = the natural logarithm of MVE at the end of the fiscal year-end prior to the announcement.

Table 5
Regression of Firm Specific Variables on Cumulative Abnormal Returns

Variable	**Predicted Sign**	**Parameter Estimate**	**White T-Stat**
Intercept		-0.0223	-1.48
Market/Book	+	0.0003	0.52
Intangibles	+	0.0246	0.92
Cash Ratio	-	-0.0395	-4.74***
EPS Vol	+	-0.0000	-0.64
Leverage	+	0.0000	0.00
Size	+	0.0028	1.87*
N		120	
Adj. R-Squared		11.1%	
F-Value		3.47	
Model Significance		0.004	

Where the dependent variable is CAR, the cumulative abnormal return for the event period, the announcement day plus the following day, computed using the Fama-French three factor model. Market/Book = the market value of the firm divided by its book value of equity reported at the end of the fiscal year-end prior to the announcement. Intangibles = book value of intangible assets divided by total assets reported at the end of the fiscal year-end prior to the announcement. Cash Ratio = the amount of cash as reported at the end of the fiscal year-end prior to the announcement divided by total liabilities. EPSVol = the standard deviation of the change in earnings per share over the eight quarters prior to the announcement. Leverage = total liabilities divided by market value of equity reported at the end of the fiscal year-end prior to the announcement. Size = the natural logarithm of MVE at the end of the fiscal year-end prior to the announcement. ***, **, *, indicates significance at the 1%, 5% and 10% levels

Table 6
Regression of Firm Specific Variables on Cumulative Abnormal Returns: Sub-samples of Financial and Non-Financial Firms

		Financial Firms sub sample		**Non-Financial firms sub sample**	
Variable	**Predicted Sign**	**Parameter Estimate**	**White T-stat**	**Parameter Estimate**	**White T-stat**
Intercept		-0.0061	-0.20	-0.0327	-1.92*
Market/Book	+	0.0023	1.49	-0.0006	-1.22
Intangibles	+	0.067	0.56	0.0317	1.48
Cash Ratio	-	-0.0499	-2.49**	-0.0405	-4.49***
EPS Vol	+	-0.0000	0.10	0.0004	3.42***
Leverage	+	0.0004	1.32	-0.0039	-3.84***
Size	+	0.0006	0.25	0.0048	2.59***
N		47		73	
Adj. R-Squared		0.50%		27.9%	
F-Value		1.04		5.66	
Model Significance		0.413		0.001	

Where the dependent variable is CAR, the cumulative abnormal return for the event period, the announcement day plus the following day, computed using the Fama-French three factor model. Market/Book = the market value of the firm divided by its book value of equity reported at the end of the fiscal year-end prior to the announcement. Intangibles = book value of intangible assets divided by total assets reported at the end of the fiscal year-end prior to the announcement. Cash Ratio = the amount of cash as reported at the end of the fiscal year-end prior to the announcement divided by total liabilities. EPSVol = the standard deviation of the change in earnings per share over the eight quarters prior to the announcement. Leverage = total liabilities divided by market value of equity reported at the end of the fiscal year-end prior to the announcement. Size = the natural logarithm of MVE at the end of the fiscal year-end prior to the announcement. ***, **, *, indicates significance at the 1%, 5% and 10% levels