REINSURANCE COUNTERPARTY CREDIT RISKS

PRACTICAL SUGGESTIONS FOR PRICING, RESERVING AND CAPITAL MODELLING

26th July 2007

2007 GIRO 'RCCR' Working Party

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Objective

To advance actuarial thinking and practice in the area of reinsurance counterparty credit risk, seeking to highlight flaws in current approaches and suggest alternatives.

Thanks!

The members of the working party would like to express their gratitude to Meirion Morgan and Erik Manning for their guidance, assistance and encouragement. We would also like to thank Kirsty Gray and Carl Overy for their helpful comments upon reviewing our draft paper.

Disclaimers

All errors, omissions and potential controversy remain the sole responsibility of the authors. The views and opinions expressed within this paper do not necessarily reflect those of all the authors or the employers of any of the authors.

The methods and approaches set out within this paper and the accompanying spreadsheet are intended solely as an illustration of one possible method of approaching the assessment of reinsurance counterparty credit risk.

We the authors do not invite reliance on, nor accept responsibility for, the information contained in this booklet nor in the accompanying workbook. Further, we do not give any guarantee, undertaking or warranty concerning the accuracy, completeness or up-to-date nature of the information contained herein and do not accept responsibility for any loss which may arise from reliance on information in this presentation or workbook.

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1 INTRODUCTION

1.1 Reinsurance counterparty credit risk ('RCCR') concerns the risk that one or more of your reinsurers might fail to pay your recoveries in a timely manner (or possibly at all). This can arise for a wide variety of reasons including contractual failure (i.e. coverage disputes etc), reserve deficiency, fraud, overstated assets, impairment of affiliate, changes in business, large market loss and others.

1.2 RCCR can be a significant issue for many insurance and reinsurance companies, particularly since often such failures happen in times of market stress, exactly when cedants are most reliant upon getting these recoveries.

1.3 In the UK, many non-life actuaries have taken a passive approach to RCCR. The techniques applied in practice have, for valid reasons, remained quite simple and unchanged for several years. With recent advances in capital modelling practices, we decided to consider an alternative to the traditional technique of applying a set of historical charge factors to a book of reserves.

1.4 Professionals in other fields (notably investment banks) handle some very similar risks. The working party explored these wider fields and attempted to adopt some of their thinking. We discuss and illustrate some of the weaknesses in current practices along the way, even if we can't solve them all.

1.5 A key part of our work is an Excel workbook that we have built to illustrate the core banking premises and how they might be applied to RCCR. This workbook is called 'Illustrative RCCR Model.xls' and you may find it useful to have this to hand whilst reading the paper. We will be releasing the model at GIRO 2007.

1.6 Our model is not perfect – primarily due to difficulties in setting parameters – but we believe the process has some merit and offers a useful adjunct to the traditional factor-based calculations. We believed that the approach taken would be easily replicated in a stochastic ICA model.

1.7 The remainder of our paper is structured as follows:

- Section 2 summarises current practice and comments on issues and weaknesses. We have restricted our attention here to actuarial practices, but in the appendices we have added some wider discussion of commercial practices.

- Section 3 outlines the approaches in wider fields. We do not describe them in great detail as there is extensive literature already available, but we refer you to some good additional reading if you wish to find out a little more.

- Section 4 discusses our model and some of the development challenges and application benefits. We compare this to some of the issues with current practices and comment on implications with our illustrative model.
- In Section 5 we illustrate a simple application of our model.
- Section 6 offers our conclusions and suggests some further avenues for additional research.
- Section 7 reports very briefly on a different avenue of research discovered at a late stage in our work.

1.8 We also include a number of appendices which we hope provide some further interest:

- Appendix A contains a summary of the 'mechanical' part of financial strength assessments followed by the major rating agencies, noting the inclusion of RCCR;
- Appendix B contains a very brief summary of the approaches taken to RCCR by Life actuaries;
- Appendix C contains a page-by-page guide to the workings of our illustrative model;
- Appendix D contains comments relating to captives and reimbursement programmes;
- Appendix E contains a discussion of a number of commercial considerations pertinent to RCCR;
- Appendix F contains some more discussion on the issue of correlations;
- Appendix G contains a number of references for further reading; and
- Appendix H contains some screen prints from our model.

2 BRIEF OVERVIEW OF CURRENT ACTUARIAL PRACTICE

2.1 Here we describe what we understand to be current practice for many UK non-life actuaries in handling RCCR. We note a few generic weaknesses in these approaches, most of which are widely known but often overlooked.

Reserving

2.2 Reserving is the area where there is the most consistency in approach. This has been attained through the excellent 'bad debt paper'[1] that was presented to GIRO in 2000, updated in 2005 and adopted as an Advisory Note for actuaries signing US Opinions.

2.3 The 'bad debt paper' can be found on the Actuarial Profession website[2] and is essential reading for anyone new to the subject. The paper describes a wealth of relevant considerations en route to their proposed approach.

2.4 The 'bad debt paper' promotes a factor-based deterministic provision, i.e. expected recoveries multiplied by charge factors, where the factors are based on corporate bond default rates with adjustment for anticipated recovery rates.

2.5 For example, suppose you had \$100m of recoveries due from a group of reinsurers each with an 'A' credit rating from a well respected rating agency and \$50m from another group of reinsurers with a 'BBB' rating. Based on the default tables methodology you might adopt a charge factor of, say, 2% for 'A' rated companies and 5% for 'BBB' rated. Your bad debt provision would then simply be \$100m x 0.02 + \$50m x 0.05 = \$4.5m.

Reinsurance Pricing

2.6 Many actuaries (and underwriters) make no specific allowance for RCCR when desk pricing their ceded reinsurance[3], although some companies are now starting to explicitly allow for RCCR as a 'cost of capital' component when pricing reinsurance.

2.7 Arguably the very small reduction in technical rate when considering an A- reinsurer versus A+ might not be considered adequate compensation by some cedants for the additional risk of default, as this is an area where insurers are typically risk averse.

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[1] 'Reinsurance Bad Debt Provisions for General Insurance Companies' (2000, updated 2005), R. Bulmer et al

[2] http://www.actuaries.org.uk/files/pdf/general_insurance/bad_debt2005.pdf

[3] See Appendix E for more on commercial approaches to RCCR

Capital analysis

2.8 We are aware of a number of approaches, with differing levels of sophistication. There was a 2005 GIRO workshop on Credit Risk which suggested one approach based again on the corporate bond rating transitions. However, whilst there is some guidance (e.g. from Lloyd's) in terms of the 'minimum' approach to RCCR, to our knowledge there is still no common market-wide view of what might constitute 'best practice'.

2.9 In several countries, RCCR is an important component of the capital that re/insurers must hold. In the UK credit risk is an explicit component of the ICA calculation. When formulating the current solvency requirements the FSA considered imposing hard limits on the proportion of cessions with any one reinsurance company / group that could be included within the solvency assessment. Whilst this did not pass the consultation stage, there can be little doubt that undue concentration with any one reinsurer remains a concern.

2.10 The capital assessments performed by rating agencies like AM Best and Standard & Poor's also look explicitly at RCCR using again a deterministic factor based approach. We discuss these in more detail in appendix A.

Comments

2.11 Before we discuss weaknesses of the factor based approaches, it is worth remembering the context. If your company is strongly capitalised and has only a little reinsurance, spread amongst a diverse range of secure reinsurers, it may well be very appropriate to take a relaxed view to RCCR and spend your time on issues of greater significance to ongoing solvency and profitability.

2.12 We consider the 'bad debt paper' first published in 1999 by Richard Bulmer et al provides an extremely good introduction to RCCR, covering a wide range of issues and offering a very practical approach to assessing bad debt reserves. The solution was simple to understand and implement (see paragraph 2.5 above) and was entirely appropriate at the time.

2.13 However, now that we are in a world of ICAS and ERM, today's economic capital modelling techniques can benefit from taking a more prospective view.

2.14 Among the pitfalls we see with using a rating-agency-factor approach, perhaps the key ones are:

1. The published default and transition tables are not really appropriate to reinsurance default;
2. The past may not be a good guide to the future;
3. Inadequate allowance for accumulations and tail dependencies.

There are others too (for example, the methodology does not allow for the duration of your recoveries – what really matters is the willingness and ability of your reinsurers to pay out at some point in the future, rather than their ability today) but we will focus here on the three.

Published tables not really appropriate

2.15 Many of the rating agency transition and default tables are based on historical corporate bond credit-rating transitions and defaults, not on reinsurance payments.[4] The two processes (bond ratings and reinsurer payment performance) are very different.

2.16 We are reading a table that says something along the lines of "1 in X A-rated corporate bonds defaulted per annum on average over the last Y years", and inferring that "1 in X A-rated reinsurers are expected to default next year". In doing so we are assuming the rating agencies are consistent in their approach and ability to rate corporate bond performance and reinsurer payments, and that the experience is stable over time (both past and future). Both of these assumptions should be challenged.

2.17 In addition, with RCCR we have the 'won't pay' dynamic in addition to the 'can't pay'. Both create strain (at the very least on your cash-flow) and therefore should impact your RCCR assessment but there is no direct analogy of 'won't pay' within the world of corporate bonds nor within the tables.

2.18 Furthermore, it is widely commented that there is an element of inertia to the credit ratings (indeed the agencies have made statements to this effect in the past). Relying on this source in isolation we might expect our RCCR analysis to also be somewhat slow to react to changes in the risks.

Is the past a good guide to the future?

2.19 Regulation continues to evolve, often designed to strengthen insurance company management and therefore reduce the possible impact of RCCR. Does this mean future reinsurer disputes and insolvencies will be less common than in the past?

2.20 The causes that often trigger reinsurer insolvencies are far from constant over time in their occurrence. Large natural catastrophe losses are one obvious cause. Economic and insurance cycles also play their parts. An investment

[4] This is true in particular of the S&P and Moody's tables used in the 'bad debt paper'. Furthermore, as the 'bad debt paper' observes, the underlying bonds that drive these tables are not insurance and reinsurance specific. However, there are exception, notably from A M Best who now publish impairment and rating transition tables for US-domiciled insurance companies (only) – this can be found at http://www.ambest.com/ratings/methodology/impairment.pdf.

loss that weakens the balance sheet just before a large insurance loss will increase the insolvency probability.

2.21 Even supposing we were happy that the ‘bond tables’ *were* representative of past reinsurance defaults, based as they are on the last X years of experience why should we take this X-year average as a reliable guide to future years?

2.22 A simple comparison of the latest transition matrices to those from 5 or 10 years ago quickly demonstrates not, as has been shown before.[5] The implication is that provisions based on these tables in the past would, based on updated information, have likely turned out to be insufficient. How different will it look in 10 years time? Are provisions today inadequate, or is this a cyclical effect in the tables, or do regulatory improvements imply they would now overstate provisions?

2.23 We do not know the answer to these questions. We do know they show us that a ‘blind’ application of a rating-agency table methodology glosses over a number of important considerations.

Accumulations and tail dependencies

2.24 The field of reinsurance credit risks is littered with correlations and dependencies, especially in the tails of the distributions where it really matters:

- Shock effects: Reinsurers have significant common exposures to natural and man-made catastrophe events, and to a significant accumulation of losses arising from legislative or regulatory change. Often, at higher return periods, the correlation increases between reinsurers;

- Market-wide cycle effects: Sustained soft cycle periods lead to growing reserve issues which can subsequently emerge as credit issues;

- Domino effects: Small reinsurers can sometimes be reliant on a large reinsurer. For example, in 2007 we have perhaps 60 global property catastrophe reinsurers and only 10-15 companies assuming significant property cat retrocession. Consequently the failure of just one large cat retro writer could materially impact several reinsurers and many more insurers with it;

- Momentum: Rating downgrades have in the past often led to rating slides over a relatively short time – sometimes called the ratings ‘death spiral’ particularly once a rating falls from ‘the As’ into ‘the Bs’. Consequently a

[5] To see this you need only look at the current version of the ‘bad debt paper’. This contains S&P’s rating transition matrices through 1997 and through 2004. For example, the later table shows an approximate doubling of default rates for BBB rated companies and a near-halving of the rates for AAA rated companies.

downgrade from A- to BBB may be followed quite rapidly by closure to new business and adoption of a run-off strategy;

- Gross and Reinsurance: There can be strong interactions and correlations between counterparty default and your own loss experience (i.e. they fail just when you need them most). Typically this is a result of the other factors noted above, i.e. you are affected by the same causes;

- Temporal effects: Correlations between underwriting years due to commonality of reinsurers. This can be especially significant when writing a lot of long tailed business.

2.25 Furthermore, a factor based approach doesn't differentiate between having £100m with a single A-rated reinsurer and a portfolio of 10 lots of £10m each with a different A-rated reinsurer.

2.26 On a global basis, the reinsurance world looks both more correlated and more concentrated than the insurance world, and has been searching for geographical and class of business diversification to reduce this effect (witness the advent of Cat Bonds and other capital market instruments in recent years).

2.27 Allowing for the most important of these correlations and dependencies can significantly improve your analysis, and might have a quite dramatic impact on your output and conclusions. We will come back to this later in this paper.

<u>So what?</u>

2.28 In a world of economic capital models, ICAS and Solvency II, the deterministic factor-based approach can readily be made stochastic and used to work around some of the issues described above.

2.29 However, this 'stochastication' of the old methodology would not on its own address many of the issues we have described. We therefore felt it worth investigating other fields, notably to investment banking, to see whether we could learn any new tricks from them.

3 CONCEPTS FROM INVESTMENT BANKING

3.1 As part of our research we spoke to a number of people including practitioners at rating agencies, life insurance and investment banks and we also read some of their literature.

3.2 We have summarised the life actuary and rating agency approaches to RCCR in appendices A and B to this report. However, the core investment bank approach in particular was more interesting and worthy of further study so is summarised in this section.

3.3 Investment banks price and trade a large volume of credit related financial instruments every day. This is supported by a variety of credit models, but the core principle underpinning these models appears consistent: A stochastic model based on a Poisson default process using a time-dependant random parameter λ, known as the 'default intensity'.

3.4 Given the nature of an investment bank and the speed and size of the trades they are doing, their models contain proprietary technical finesses around this central principle. For our purposes we do not need to get bogged down in these complications, and we concentrate here on the common core approach.

3.5 The underlying premise is that the market 'spread' for a Credit Default Swap[6] ('CDS') on a company is the (forward looking) market rate for taking on the credit risk[7] over the coming years, taking into consideration all that is known in the public domain about that counterparty and its environment.

3.6 For a given counterparty, the parameter λ is therefore fitted to the market spread for a CDS on that company or, if that is not available, for a company they view as being similarly risky and with similar duration. Sometimes the analysts struggle to find a good comparator for an unlisted counterparty, so here they exercise judgment.

[6] A credit default swap is an contract between a buyer and a seller whereby the buyer pays a periodic fee in return for a contingent payment by the seller upon a credit event (typically a default or failure to pay) happening in the reference entity. For example, a CDS on Ford Motor Company could be triggered by Ford defaulting on its obligations to pay coupons on a particular Ford bond. So, buyer pays seller a regular fee for a period of time, typically 5 years, and if Ford defaults on this bond within this term the seller pays the buyer a pre-determined amount, and if Ford do not default the seller doesn't pay anything.

[7] This assumption can be weak in some cases. In particular, for particular CDS instruments that are infrequently traded there can be a margin within the spread that derives from liquidity issues as well as the default risk itself. The true 'market assessment' of the credit risk in such cases is therefore less than the spread so as (forward looking) estimates of default risk these will be slightly conservative.

3.7 For example, suppose that for Company ABC there were digital[8] CDS's being traded with each of 1, 3 and 5 year duration at respective spreads of 40, 45 and 55 basis points.

- In approximate terms (and ignoring the liquidity issue) this means that the market consensus is that there is a 0.4% annual probability of default on a 1 year duration, a 0.45% per annum probability over 3 years duration and a 0.55% per annum default probability over 5 years duration.

- We can interpolate or extrapolate for estimates of the market-consistent default rates over different durations, or we can fit a curve through the points. This curve fitting is effectively the backbone of what the banks do.

3.8 A related market statistic you might also consider is the additional yield available on a corporate bond over and above the risk-free rate at the same duration. For example, if Company A also had some 3 year duration-to-expiry bonds in issuance we would expect these to trade at a price such that the yield margin above risk-free reflected the default risk (and possibly liquidity etc).

3.9 Market spreads look forward and include far more recent information than the historical tables published by rating agencies. Of course, they are also set in a world that knows all the credit ratings, and also the rating agency historical default rates and transition matrices so you might argue they capture that information too.

3.10 Several papers have been published[9] over the years within the investment banking community regarding the occasionally large differences observed between market default yields (higher) and historical default rates (lower), seeking reconciliation between the two. However, over the last couple of years the benign credit environment has seen spreads shrink enormously so the extent of the market - historic differential has changed accordingly.[10]

3.11 The banks fit a 'yield curve' of default intensities (the spreads) against time, using whatever data they can get from the market. This requires judgment as the number of good data points available is often less than ideal. We are told that the advent of 'MarkIt Partners' has helped here - although not perfect, their provision of daily marks for default curves has helped enormously.[11]

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[8] 'Digital' meaning that the full notional value is paid upon a default event of the corresponding reference credit. So if you hold £100 notional of CDS and the reference stock defaults, you receive a full payment of £100.

[9] E.g. 'Bond Prices, Default Probabilities and Risk Premiums' (2005) by Hull, Predescu and White

[10] At the time of the referenced academic analysis, spreads were a lot wider and hence the differential was a lot greater. The key underlying premise (that the spreads are a proxy for the prospective view of default risk) therefore continues to underpin the models used in practice.

[11] http://www.mark-it.com/marketing/index.php

3.12 The spread varies significantly from risk to risk even within a credit-rating band. This variation is due to supply and demand, which in turn is driven largely by the market view of the default probabilities for each risk – all 'A' (or whatever) rated risks are not deemed equally risky by the market.

3.13 Furthermore, this variability increases as the credit rating decreases. The difference in spreads between C-rated risks is much greater than that between A-rated, and so on. (Some of this additional variability is believed to be explained by greater liquidity concerns on these stocks but there are still significant differences between the market views of default risk.)

3.14 When modelling a basket of risks, banks model each constituent and then aggregate allowing for correlations. There seems to be a move within the banking community in favour of copulas to model these dependencies.

3.15 A number of books offer a detailed guide to the pricing models used in the banking world and cover the mathematics in some detail, including:

- Cox processes (stochastic models with random parameters)
- Use of Martingales (stochastic models with a memory)
- Markov chains, transition matrices
- Merton models and Moody's KMV (lots on this on the web…)
- Dependency modelling

3.16 Two books we found useful introductory reading are 'Credit derivatives pricing models'[12] by Schonbucher, and 'Credit risk measurement'[13] by Saunders and Allen, but there are many others available.

3.17 We have developed an illustrative RCCR model using these basic investment-bank approaches and will describe this in more detail in the next section.

[12] ISBN: 0470842911

[13] ISBN: 047121910X

4 OUR ILLUSTRATIVE MODEL

4.1 We developed an excel workbook to accompany this paper, the 'Illustrative RCCR Model', solely for the purpose of testing some of these ideas and illustrating how they might be used in practice. We have made a copy of this workbook freely available and encourage the reader to play with it in conjunction with this section of our paper.

4.2 In order to keep our model explanation simple we have constrained ourselves to a small data set and number of reinsurers, but clearly this could readily be extended to accommodate a more realistic situation.

4.3 Our model is provided for the sole purpose of illustrating and exploring ideas and we do not invite reliance on, nor accept responsibility for, the information contained in this model. Further, we do not give any guarantee, undertaking or warranty concerning the accuracy, completeness or up-to-date nature of the information contained herein and do not accept responsibility for any loss which may arise from reliance on information in this model.

4.4 We have included a guide to the mechanics of the model in appendix C as well as some screen prints in appendix H. Please refer to these (and to the workbook itself) for an explanation of how it works.

4.5 We focus here on a description of the methodology, a discussion of the key hurdle developing this model, and a review of the main benefits to be had from our suggested approach. In section 5 we will go on to provide some example outputs from application of the model based on the screen prints in Appendix H.

<u>Description of core methodology</u>

4.6 The approach is to use market data on CDS prices (or on yield margins on corporate bonds over and above risk-free rates) to guide the selection of prospective default intensity curves by cohort of reinsurer, then to build a simulation model using these.

4.7 Next we fit curves to these point values to get a 'yield curve' of default rates looking forward over the remaining term of our reinsurance liabilities. This then becomes a key assumption in a stochastic cash-flow model of the run-off of the recoveries.

4.8 In this model we allow explicitly for some of the key drivers of correlations and accumulations relevant to RCCR and its impact on a cedant. We model some simple 'cause and effect' directly as these can be a key component of the correlations.

Market data for default intensities

4.9 The biggest challenge in developing this model is getting market data to use for the default intensities, or more accurately, it is identifying market instruments that can be used as proxies. Once the securities are identified market data is readily available on the web, notably from Bloomberg and Reuters, although you will probably need to subscribe to an information service (or know someone who does) if you want live updates.[14]

4.10 One particular issue is the selection of reference companies, as there are relatively few reinsurers with significant traded bond or CDS issues. You may wish to spend a little time considering how to benchmark against those that are traded, together with spreads for non-reinsurance companies with the same credit rating.

4.11 One possible approach to identifying appropriate reference companies that are non-reinsurers, might be to identify companies with the same credit rating and a similar coefficient of variation in share price movements as the reinsurer. We have not yet investigated whether the CoV in share price is an appropriate comparison point, so this is offered as a theoretical possibility rather than any form of recommendation.

4.12 Of course, should you not wish to use the market data you can always generate your own default intensity curves based on analysis of the rating agency default tables, with suitable adjustments.

Dependency inputs

4.13 As already noted dependencies and correlations play a key part in the world of RCCR and should not be ignored. We believe there is merit in breaking these correlations into two parts – those that are fundamental and stand a chance of being modelled, and those that are not.

4.14 The first category contains shock events such as natural catastrophes, major terrorism losses and so on. We believe it also contains the reinsurance cycle. In our model we have therefore incorporated some simple direct dependencies for both of these effects.

[14] If you do not have a subscription (we understand Bloomberg costs around $1,000 per month), you may find that your CFO or your company's bankers and investment advisors have subscriptions.

4.15 For shock losses we simulate an event trigger with a user-defined probability, and when it happens we increase all reinsurer default probabilities for a period of time, again controlled by the user. The increase in probability can be greater for companies with lower ratings at the time of the simulated event. For example, you might choose to increase all default probabilities by a factor or by an additive uplift or by some combination, for a couple of years. Selection of these parameters is a matter of judgement, but the analysis of rating changes following the World Trade Center and Hurricane Katrina may be of use in this assessment.

4.16 For the cycle we again simulate an increase in all default probabilities but over a longer period of time and with greater likelihood. Again this calls for judgement and we include the feature as much to illustrate one way you might readily do it, rather than to propose that our approach might be the best one.

4.17 By directly manipulating the defaults in this manner we are starting to address some of the weaknesses in the traditional approach. We have control over the default probabilities, we can vary them over time, we subject them to common forces and we allow for some of these effects to work over a number of years.

4.18 If you already have a stochastic model of your portfolio, for example as part of your ICAS work in the UK, you could (should?) also introduce some additional correlations to your simulated gross underwriting results. The occurrence of major catastrophic events should be reflected simultaneously in both the RCCR and the gross event losses. Additionally the reinsurance cycle is linked to, albeit slightly out of phase with, the insurance cycle – so again this is likely to be having most adverse impact on default rates at the time where it is also having an adverse impact on gross profitability of the insurance business. At the very least it would seem the catastrophe shock should be ‘connected’ to the cat losses in your gross event generation.

4.19 The second group of dependencies mentioned above (those which are less direct and therefore harder to model explicitly) might be allowed for with some correlation matrices or other aggregation techniques, but we have not attempted to do this here for two reasons: simplicity is one, and also we suggest such additional correlations might be spurious in the real-world given the number of assumptions required to model RCCR.

Comments

4.20 The rest of the model is largely mechanical and of course we have simplified a number of features in order to focus on the methodology. It would be relatively simple to also build in such features as future reinsurance premiums (with offset, if appropriate) and to extend the number of buckets sufficient for a real analysis.

4.21 We believe the model offers the following advantages over the traditional approach:

- You have a stochastic model that can play a useful role within your capital and ICA modelling;
- You are thinking about and actively modelling the key dependencies, including an explicit consideration of how they might change over time;
- You are thinking about how skewed the distribution should be and how bad the outcomes might be;
- You are making a conscious, prospective decision about default intensities, rather than relying predominantly on (inappropriate) historical tables;
- In doing so you are factoring in issues such as 'won't pay' rather than simple black-and-white defaults;
- You are possibly starting to take into consideration some new investment market data;
- You are assessing the (potentially very real and under-estimated) cash-flow strains that can be a feature of reinsurance credit in addition to the failures.

Comparison to previous common approaches

4.22 The above list of advantages summarises some of the benefits from our suggested approach. However, we are not saying that it should necessarily replace the traditional methods; we simply hope that our model provides an interesting and we hope useful additional perspective.

4.23 If you find that our model produces a significantly different estimate to your 'traditional' calculations, this will of course be due largely to differences in the underlying assumptions, in particular between the default intensities and the historical default rates. Investigating and attempting to narrow this difference can be enlightening, so long as you don't start with a premise that only one of the two models is inherently 'wrong'.

4.24 If this does nothing more than highlight to some that their RCCR provision might be significantly wrong, this is a good thing. After all, thinking back to our opening paragraphs, why are we so sure the default tables are appropriate anyway?

5 EXAMPLE APPLICATION OF THE MODEL

5.1 Appendix H contains screen prints taken from our model which we have used to analyse the following data:

- Reinsurance recoverables of 10,000 split into three buckets of reinsurers: 3,450 in Bucket 1 ('B1') with an AA-rated reinsurer; 5,550 in Bucket 2 ('B2') with an A rated company and 1,000 in Bucket 3 ('B3') which is an unrated company. These recoverables are spread over a number of years of account;

- We have assumed a consistent runoff payment pattern for each year of account (in the absence of any default):

Year	%	Cumulative
1	5	5
2	10	15
3	15	30
4	20	50
5	15	65
6	10	75
7	10	85
8	5	90
9	5	95
10	5	100

- In the Default Intensity Selection sheet we have for illustration shown CDS spreads for AIG, QBE and XL Capital as well as for a couple of hypothetical companies with lower credit ratings. We have used these to guide our selection of default intensity curves for our three buckets, which are approximately 0.1% per annum for B1, 2% per annum for B2 and 10 to 20% per annum for B3. We have also assumed mean recovery rates post-default of 60%, 50% and 45% respectively and mean additional delays post-default of 3y, 3y and 5y respectively.

- In "Dependencies" we have elected to simulate a 1 in 100 cat event straining the reinsurance security by increasing all default probabilities 'x' to 3'x'+5% for 3 years post-cat. We have also chosen to simulate a random cycle-related strain with a 90% likelihood of occurring in the next 10 years that would increase probabilities to 2'x'+1% for 3 years.

5.2 The next five sheets of the model calculate the quantum and the timing of the recoveries and resultant cash-flow strain based on the simulated variables in the preceding sheets.

5.3 The simulation results show us that, under our assumptions, the mean 'loss' through bad debts amounts to 285 which equates to the 70th percentile of the distribution.

5.4 It also gives us a number of other points from the distribution which could be of interest in the context of capital assessments:

Mean	285
70%	285
95%	1,011
97.5%	1,479
99%	2,843
99.5%	3,017
99.9%	3,325

5.5 Of course we could also read off other interesting metrics, such as the probability of having no bad debts (19% in this case), or the expected cash flow strains in the event that there are some bad debts, or the probability that your available credit for such eventualities might be breached.

5.6 On the final page we have applied the traditional rating agency factor-based approach to the same data in line with the 'bad debt paper'. This produced a provision of 320.

5.7 The fact that 320 is higher than 285 should not be interpreted as prudence within the factor based approach, it is simply the way the numbers worked out on this simplistic illustration. We would suggest that the next step would be to investigate and understand the difference before deciding upon your provision.

5.8 For example, in this case we can see that a large part of the difference is likely to stem from Bucket 3 where the 'old' method simply wrote off 50% whereas our 'new' method used a default probability nearer to 20% per annum on the reducing balance as liabilities were settled. If B3 are still paying claims and you have no cause for concern, this might be more appropriate than simply writing off 50%. On the other hand, if you do have concerns about B3, perhaps you should choose a more severe default intensity curve under the 'new' method.

5.9 Also of interest is the impact on the 'loss' from delays in receiving (partial) payments from defaulted reinsurers. If we look at the mean NPV of defaulted recoveries as a proportion of the mean NPV without default, in our illustration we get an 'economic' loss rate of 3.2% compared to the 'undiscounted' 2.8%. Therefore, in this simple illustration, the delays serve to increase the cost by 12.4% which might lead you towards provision of 319[15] rather than 285.

[15] The amazing closeness of 319 to 320 is pure coincidence, we didn't set out to engineer this, honestly!

6 SUMMARY AND CONCLUSIONS

6.1 Our stated objective was to attempt "to advance actuarial thinking and practice in the area of reinsurance counterparty credit risk, seeking to highlight flaws in current approaches and suggest alternatives".

6.2 In this paper (and through our illustrative model) we hope we have raised awareness amongst readers of both the issues surrounding current analysis of RCCR, and also of possible alternative approaches to some of these problems.

6.3 The default tables are based on historical experience (that might not represent future exposure) of corporate bond failures (not the same as reinsurance default). The traditional application of these tables does not allow for key dependencies and correlations within the bad debt provisions and also between possible failures and the gross underwriting result.

6.4 We offer a model that captures some of the key dynamics in RCCR and so starts to address some of the common issues.

6.5 At the same time we attempt to parameterise this model with prospective default estimates with reference to investment data on CDS spreads and/or bond yield margins. We find this parameterisation process to be challenging due to scarcity of directly relevant market data. However, we found the thought process helpful and hope that others might too.

6.6 Whilst thinking about this last statement, it is also worth remembering that the data in the rating agency tables is also a lot less relevant than it might sometimes be considered.

6.7 We hope you enjoyed reading our paper. As a challenge for the more interested reader, we suggest a topic for further research lies in choosing the parameters for RCCR models such as ours:

- What else can we gain from developing a more detailed understanding of the banking products and market prices?
- Can we infer anything from technical analysis of reinsurer equity prices?
- Do D&O or Credit underwriting techniques offer any additional clues?

6.8 Our model is far from perfect, but what model isn't? The world is complex and unpredictable. We hope our paper offers some interesting perspectives and a worthwhile addition to the actuarial toolkit. At the very least, playing with the workbook and thinking about its relative strengths and weaknesses should prove a worthwhile pursuit for anyone not already expert in RCCR.

7 LATE DEVELOPMENTS

7.1 Just before going to press with this paper we learned of some potentially interesting and relevant analysis being performed by a company called Arium. Arium is developing a predictive model to identify 'high risk debts', i.e. debts least likely to be paid on time.

7.2 Arium have performed a preliminary statistical analysis of the actual time it took reinsurers to pay receivables in a number of insurance portfolios over a five year period. They tested a variety of parameters for significance such as line of business, the identity of the broker and reinsurer, size of debt, number of reinsurers per contract, reinsurer's credit rating and changes in that rating.

7.3 Once further analysis and validation has been carried out, Arium hope the results could be used to predict payment time for a receivables portfolio. These results could also be, and should continue to be, validated on other receivable portfolios.

7.4 The results might also be used in a model to identify which portfolios of receivables are vulnerable to an accumulation loss on the basis of having a concentration of high risk debts. Arium takes line of business into account as well as the reinsurer in this diversity model.

7.5 Unfortunately due to the late timing of this 'discovery' we have not been able to investigate further as yet, but interested actuaries might start by looking at Arium's website: http://www.arium.co.uk/

APPENDICES

A. RATING AGENCIES

B. TECHNIQUES USED BY LIFE ACTUARIES

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APPENDIX A

RATING AGENCIES

All the major rating agencies publish papers outlining their core approaches and methodologies for assessing the financial strength of a company when awarding a credit rating. The rating agencies focus on a large number of similar areas to derive a capital adequacy measure. These encompass both objective and subjective factors but the process is reasonably transparent.

In the table below we have summarised some of these components for the 'big four' agencies. Within their assessment of the financial strength of a re/insurance company all the agencies study the reinsurance asset in terms of its size and quality (as measured by their own ratings!) Furthermore, all the agencies anticipate some kind of increased stress to the RCCR as part of the 'nat cat' assessment. A lot more detail is readily available on the internet[16] or directly from the agencies.

One recent development we have heard is that S&P is due to introduce a new ratings system for re/insurers in run-off, with a 1+ rating indicating the highest expectation of the recovery of principal in the event of a default and a rating of 5 indicating a zero to 25% chance of recovery of principal.

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[16] For example, see http://www.ambest.com/ratings/pcbirpreface.pdf

	A. M. Best	S&P	Fitch	Moody's
Economic Capital Model				
1. Type of Model	Deterministic	Deterministic	Stochastic model called PRISM	Deterministic
2. Key Component	1. BCAR Financial Strength (50%) 2. Operating Performance (20%) 3. Business Profile (20%)	1. CAR 2. Operating Performance 3. Organization's enterprise risk management practices (ERM)	The model determines capital adequacy using a stochastic measure of required capital. 1. Assets 2. Credit 3. Underwriting 4. Loss reserves 5. Operational risks 6. Natural catastrophes	1. Business profile factors (33%) 2. Financial profile factors (66%)
3. Definitions	BCAR = Adjusted statutory capital/Required capital Adjusted statutory capital is the reported surplus plus/minus adjustments made to provide a more comparable basis for evaluating balance sheet strength. Such modifications include: - Equity in unearned Premium and loss reserves;	CAR =(total adjusted capital – investment related charges – other credit related charges) / (underwriting risk + reserve risk + other business risk) The calculations begins by adjusting booked capital to a more realistic basis (for example, by adjusting for hidden asset values and reserve adequacy) to determine total adjusted		Gross underwriting leverage (gross written premium plus gross reserves divided by shareholders' equity) is used for the predictive ratio for capital adequacy.

	- Redundancy or deficiency in loss reserves; - Market vs book value of fixed income portfolio	capital (TAC). TAC is then reduced by charges to reflect realistic expectations of potential losses arising from credit risk and investment market volatility risk. The resulting level of capital is compared with a base level of capital appropriate to support the ongoing business activities.		
4. Rating Category	A++, A+, A, A-, B++, B+, B-, B, C+, C++, C-,C	AAA, AA, A, BBB, BB	AAA, AA, A, BBB, BB	Aaa, Aa, A, Baa, Ba
5. Ideal Scores	**Rating** **BCAR's Score** A++ >175% A+ 160%-175% A 145%-160% A- 130%-145% B++ 115%-130% B+ 100%-115% B-/B 80%-100% C+/C++ 60%-80% C-/C 40%-60%	**Rating** **CAR** AAA >175% AA 150% - 174% A 125% – 149% BBB 100% - 124% BB < 100%	N/A	**Rating** **Gross leverage** Aaa <2 Aa 2x - 3x A 3x - 5x Baa 5x - 7x Ba >7

	A. M. Best	S&P	Fitch	Moody’s
Treatment of Natural Catastrophic Risk				
1- Adjustment to Capital for Cat. Risk Exposure	Capital reduced for the higher of the 1/100 wind or 1/250 earthquake net PML (occurrence basis)	Capital increased for 1/250 net PML (aggregate basis). Net of one year’s catastrophe premiums written less 30% for expenses	Capital includes an amount based on tail value at risk (TVaR) from the catastrophe loss exceedance curve. The TVaR thresholds have not yet been determined but will vary based on a company’s rating level.	Capital in simulation iterations include amounts generated from random draws of exceedance curves for 7 US catastrophes. Overall required capital is set at the enterprise loss amount at the 1/1000 return time.
2- Measurement	Event	Aggregate	Aggregate	Event
3- Modelling Horizon	5 year horizon	5 year horizon	Waiting to see the impact of the near/medium term frequency assumptions on some companies before making determination as at April 2007	5 year horizon
4- Components of Loss	• Demand Surge, • Storm surge • Fire following earthquake • Secondary uncertainty • Loss adjustment expenses.	• Demand Surge, • Storm surge • Fire following earthquake • Secondary uncertainty • • Sprinkler leakage	• Demand Surge, • Storm surge • Fire following earthquake • Secondary uncertainty • Loss adjustment expenses.	• Demand Surge, • Storm surge • Fire following earthquake • Secondary uncertainty • Loss adjustment expenses.

	A. M. Best	S&P	Fitch	Moody's
5- Reinsurance assumption in Catastrophic Risk Change	Net of reinsurance plus reinstatements and co-participations	Net of reinsurance plus reinstatements and co-participations	Net of generic or company specific reinsurance (if the company provides information)	Assumes 90% cession for losses between the 1/25 to 1/100 levels.
6- Credit Risk Impact	Stress test adds credit risk charge by applying the credit factor to 80% of ceded reserves from first event and by assuming one level downgrade **<u>Rating</u>** **<u>Credit Factor</u>** A++ 2% A+ 4% A 6% A- 10% B++ 15-20% B+ 15-20%	Potential material increases in reinsurance recoverable taken into account (analyst discretion)	The model can be set to assume that the catastrophe reinsurers are highly rated, the (prospective) underwriting risk is reinsured by relatively highly rated reinsurers and the existing loss reserves are reinsured by weaker reinsurers. This is done to account for the possibility that the loss reserves may have been reinsured five or more years ago by reinsurers whose credit ratings have deteriorated since then.	Ceded losses are considered reinsurance recoverable and added to reinsurance risk which is part of the rating process.
7- 2nd Event Stress Test	Calculate a stressed BCAR including a 2nd net catastrophe PML at the higher of the 1/100 wind or the 1/100 earthquake	Believed to be not applicable as aggregate net PML information is used.	Believed to be not applicable as aggregate net PML information is used.	Add randomly generated catastrophes from the seven areas so this included multiple events, but not necessarily second event in same region or peril.

	A. M. Best	S&P	Fitch	Moody's
ERM				
1- Separate rating category	No (implicitly considered within capital strength, operating performance and business profile categories)	Yes	No	No
2- ERM Rating	Not applicable	Yes (Excellent, Strong, Adequate or Weak)	Not applicable	Developing risk management assessment reports that will characterize ability as strength, neutral or weakness
3- Consideration of ERM in Rating Process	Already considered part of its procedures in evaluating capital strength, operating performance and business profile	Extent of consideration depends in part on company's abilities to absorb risks and its complexity of risks	Already considered in PRISM model	Already considered part of its procedures in evaluating capital strength, operating performance and business profile
4- Weighting of Models	Best will determine weight between BCAR and company's own model	Not available as at April 2007	Fitch will weight subjectively between PRISM, company's own model and regulatory capital requirement	Not available as at April 2007

Bibliography

- Guy Carpenter's Rating Agency Update November 2006
- An explanation of A M Bests's rating system and procedures 2006 edition.
- Moody's Global Rating Methodology for Property and Casualty Insurers September 2006
- Enterprise Risk Management for Insurers and Prism's Role September 2006
- Exposure Draft: Insurance Capital Assessment Methodology and Model (Prism) – Executive Summary, June 2006
- Exposure Draft : Prism – Insurance Capital Model – Technical Document, June 2006
- S&P's Criteria: Revised Insurance Capital Adequacy Credit Risk Measures

APPENDIX B

TECHNIQUES USED BY LIFE ACTUARIES

A range of approaches are taken to RCCR in the context of reserve setting, but it was not a consideration for product pricing due to the nature of life business. The reserving practices varied from doing nothing at all at one extreme, through to something approaching current GI thinking at the other:

- Some life actuaries literally do nothing on the basis that they believe the default probabilities of their (very strong) reinsurers is so low that it lies beyond the threshold of the VAR test they use for capital, and as such has no impact on their calculations. Of course, in doing so they are also ignoring downgrade risks but that's another story.

- Some use a higher discount rate to reflect the risks, which may be simplistic but it at least applies bigger discounts to more distant recoveries and has some intuitive feel to it.

- Some use a basic 'percentage of notional' write-down approach to make an entirely subjective allowance.

- Some ignore the smaller exposures and focus only on the larger sums at risk, yet others will take the view that there's no point worrying about these largest sums because in the event of a default from these reinsurers they would be dead anyway!

- Some treat the reinsurance cash-flows as a defaultable corporate bond and follow the statutory capital rules for those.

- A lot of companies do some 'what if' scenario testing, such as market shocks and/or failure of their biggest reinsurer, and use this to determine a provision.

RCCR is less of an issue for most Life companies since (a) they are less reliant upon reinsurance and (b) what reinsurance they have tends to be with very strong reinsurers. As such they do not suffer quite the same problems with RCCR as some general insurance companies, hence the more relaxed approach.

APPENDIX C

USERS GUIDE TO OUR ILLUSTRATIVE MODEL

A key part of our work is an Excel workbook that we have built around the core banking premises to show how they might be applied. This workbook is called 'Illustrative RCCR Model.xls' and a copy is freely available from the authors for illustrative purposes only.

We recognise this model is far from perfect – primarily due to difficulties in setting the parameters – but we do believe the process has some merit and offers a useful adjunct to the traditional factor-based calculations.

The model is built using the @Risk simulation add-in software published by Palisade. If you do not have @Risk you can readily obtain a free trial version on the internet[17]. Alternatively it should be easy to identify and understand the @Risk functions in the workbook and substitute them with your own stochastic functionality

The workbook contains the following sheets, which we will explain in turn:

- Cedant Inputs
- Risk Free Yield Selection
- Default Intensity Curve Selection
- Dependency Inputs
- Bucket 1, 2, 3
- Totals
- Cash flow Strain
- Output
- Compare Traditional

Cedant Inputs

Here we enter the estimated future recoveries by 'bucket' of reinsurer. Since this is an illustrative model, we have used only three buckets but this could readily be expanded for practical application. When choosing how many buckets to use, note that by grouping reinsurers into buckets you are effectively assuming perfect correlation between all reinsurers in each bucket.

[17] http://www.palisade-europe.com/trials.asp

We also make assumptions here about the reinsurance recovery payout patterns (absent any default) and about the 'cost of capital'. We have used the same pattern for all but you might readily vary this by reinsurer to allow for significant differences in the ceded portfolios (e.g. by class of business, attachment point, maturity etc).

The cost of capital assumption will be used later when assessing the NPV impact of defaults. We use the cost of capital because reinsurance default effectively leads to equity being used to support the liabilities.

Risk Free Yield Selection

We use the risk-free yield curve later in the workbook combined with the CDS spreads to get a 'defaultable yield' and to impute annual default probabilities.

Default Intensity Curve Selection

In the upper half of the sheet we enter market CDS spreads for a selection of traded risks. This can be obtained from sources such as Bloomberg and Reuters. Please note we have selected a few CDS examples to illustrate the process. It is unlikely you will be able to find CDS prices for your reinsurers as so few are currently in issuance. As such you must use alternative sources of guidance such as bond yields (i.e. the margin over risk free) or proxies from non-reinsurer CDS issued by appropriately rated companies.

In the lower half of the spreadsheet you make subjective judgements about the default intensity curves for your reinsurer buckets, taking guidance from the market data shown above. If this sounds a bit like you are 'making up' the key parameters, that's because you are, albeit on a logical basis thinking about the future process and in the context of market information on similarly rated investment instruments.

We also enter assumptions about expected recovery post-default and the model puts some arbitrary variance around this. This is no different to the judgement you should be making with your current methods, and we have used something close to 50% as a working assumption. Post-loss recovery is a subject in itself…

Dependency Inputs

There are significant correlations between counterparties in the extreme scenarios of reinsurer default, which are driven in no small part by shock losses and by the underwriting cycle. We model these dependencies simply but explicitly and this sheet is where you can enter your chosen parameters.

These two are not the only reasons why correlations exist between reinsurers. For example, fraudulent activity might lead to the downfall of a reinsurer and this collapse might seriously impair other companies who were heavily reinsured by it. Should you wish to you might use some correlation matrices to allow for such additional drivers but we have chosen not to in the interests of simplicity.

Bucket 1, 2, 3

For each bucket we first calculate the expected reinsurance cash flows over time.

Next we impute default probabilities from the risk free and the default intensity curves. 'ZCB' stands for 'zero coupon bond' so for a given term 't' and yield 'i' this is simply $(1+i)^{-t}$ i.e. the price now at market yields for a payment of 1 in t years time.

The ratio of ZCB prices with and without default (i.e. based on a risky yield versus a risk free yield) tells you the expected probability of default over the t-year period.

For example, consider two ZCBs each with a 3 year term: one is risk free and offers a yield of 5% per annum, the other is defaultable and offers a yield of 7% per annum. In the event of default the latter bond pays nothing. The risk free ZCB is trading at 0.863 (i.e. 1.05^{-3}) whereas the risky ZCB is trading at 0.816. The cash flows are the same so this implies the market believes there is a 94.6% chance (0.816 / 0.863) of getting paid on the risky bond.

If you are working from corporate bond yields instead of CDS spreads, it is a straightforward modification to our model to input these into the 'Defaultable yields' cells bypassing the CDS entries altogether.

Next we decompose this series of cumulative survival probabilities to arrive at the probabilities of default in each year.

In the 'default simulation' section we apply our shock and cycle impacts. We do this by simulating uplifts to the default probabilities as a consequence of shocks and cycles. We apply this same impetus across all buckets simultaneously and we stretch the impact over a number of years.

The adjusted default probabilities are then used to occasionally trip a 'defaulted' switch. We assume that once a bucked has defaulted it stays defaulted, and the 'default state' flag moves from 0 to 1 for all subsequent years.

A partial recovery rate and additional payment lag from defaulted reinsurers are both sampled and applied in order to calculate the recoveries actually made net of any default, and the net present values (discounting at the cost of capital rate).

Totals

Simple addition of the buckets input and output.

Cash flow Strain

It is worth noting that the cash flow strain on the cedant following a significant reinsurance default can temporarily exceed the ultimate loss. We model this here.

First we summarise the expected cash flows without default. Think of these as that part of the total gross losses which the cedant is hoping to collect from the reinsurers. This is 'outflow'.

Next, for each bucket, we take the actual recoveries made (net of default) together with the simulated payment lags. Using these we lay out the post-default recovery cash flow the cedant will actually get. This is 'inflow'.

Cash flow strain then takes the difference between the out- and in-flows being the strain on the cedant. We calculate the strain each year, the cumulative strain, and the maximum strain (being the peak of the cumulative strain).

With no default the two streams coincide and there is no strain. When there is a default the strain will end at the overall amount of lost recovery, but it often develops first to a larger amount (due to the payment lags) and then drops back[18].

Cedants have to pay gross claims as they fall due. Where applicable, they also have to maintain gross reserves in US situs trust funds. This peak cash flow strain is a very real number because the cash has to come from somewhere.

Output

These are @Risk summary output reports for cells of interest, namely the total amount defaulted and the peak cash flow strain.

The mean of the amount defaulted (or the 75% percentile, or whatever) might be used as a reserve provision for bad debts. The tail of this distribution might help you with your capital requirements analysis.

The peak cash flow strain output could be used to inform decisions regarding the need for any contingent temporary cash sources.

[18] To see this in the model, using @Risk, within the 'simulation settings' sampling tab, set 'standard recalc' to Monte Carlo. Now hitting F9 repeatedly will step you through simulation iterations and you should be readily able find one that has this property. It may be that you need a large catastrophe event to trigger this, in which case try entering an artificially high cat probability.

Compare Traditional

Here we have calculated a simple bad debt provision for the same book of reinsurance by using the traditional approach of Reserve x Factor based on corporate bond default rates.

This is a static, deterministic estimate that might provide some useful context for the output of the stochastic model.

APPENDIX D

CAPTIVES AND REIMBURSEMENT PROGRAMMES

The credit risk in captive fronting deals is not dissimilar to the reinsurance credit risk described in the paper. However, there are some additional issues associated with the involvement of the captive in between the fronting insurer and the reinsurers in the panel.

The significance of these issues depends on the amount of the risk retained by the captive as well as its nature, length of tail and volatility. Long tail business creates a concentration of credit risk, which builds up from successive renewals. When the fronting insurer handles the gross claims, the reserving philosophy of the fronting insurer impinges on the assessment of credit exposure to the captive.

Considering the limited ability of captives to diversify the cost of large claims, the incidence of large claims at an inopportune time for the funding parent is likely to challenge the applicability of default probabilities assumed at the back of internally assessed credit ratings, which are often pitched against default probabilities published from the big rating agencies.

In the case of gross cessions, captive involvement is likely to delay the process of recovering funds from the panel reinsurers, which in turn increases the credit risk exposure to the panel.

Captive programs usually involve direct or indirect stop loss protection (usually by means of operating aggregate deductibles). Although this type of protection acts as an upper limit for the underlying credit risk exposure, it does complicate the assessment of the credit risk exposure to the reinsurance panel as the higher layers may drop or stretch.

The risk transfer premiums are rarely good estimates of the relevant exposure to risk.

In cases where captives assume risk for which commercial insurance and reinsurance may not be widely available the volatility of the captive risks may be hard to assess unless underwriting insight is available. This will affect the credit rating and impinge on the fronting insurer's decisions on the type and mix of collateral requirements.

In setting the credit rating of a captive, analysts will usually consider the rating of the parent as an upper limit. This may lead to overstating the relevant credit risk.

For gross cessions involving long tail business, the credit risk from a captive allowing for past years exposures depends on changes in the credibility of past reinsurers. The difficulty in predicting future changes to credit ratings and the fact that fronting insurers can only charge for the assumed risk at the outset, it creates a pricing challenge.

APPENDIX E

COMMERCIAL CONSIDERATIONS

This appendix overviews a number of commercial considerations that can affect the assessment of RCCR and / or the insurer's perspective of either a specific reinsurer or a specific contract. It does not provide an in-depth review of any of these considerations, and should be regarded purely as an introduction to this side of RCCR.

Reinsurer selection & cession caps

Each insurer will set guidelines as to what constitutes acceptable security for ceded reinsurance. In the past this might have been as simple as requiring that reinsurers maintain at least a minimum specified rating from AM Best or S&P. However, the process is now both more sophisticated and more specific.

Insurers will have a list of named reinsurers to whom they are willing to cede their reinsurance; this list is often shorter for long tailed business lines than for, say, property risk or marine hull. Additionally the insurer may set caps in terms of ceded premium, limit and / or total expected recoveries (including the recoverable element of reserves) for each of these reinsurers.

When selecting both reinsurers and the respective caps the insurer will consider many factors in addition to the commercial security rating. The following list provides some examples, but is by no means comprehensive:

- It may undertake its own analysis of reinsurer strength based on publicly available information
- It will take into account its own past experience and the market reputation of the reinsurer on willingness to pay claims promptly, and the number of disputes the reinsurer becomes involved in.
- It will consider the length and strength of its relationship with the reinsurer
- The level of outstanding / IBNR recoveries will also be taken into account, as an insurer may use current placements with a reinsurer as leverage to ensure that claims on past years are paid promptly.

Reinsurance price

Within the subscription market there is no price adjustment based on security; all reinsurers who are considered adequate security for a risk will receive the same rate, irrespective of their rating. In some cases a specific reinsurer may be required to post a letter of credit (LOC) at least the value of their share of the ceded premium in order to become acceptable security to a cedant, but subject to providing this will receive the same rate. However there is an element of implicit differential pricing in that some of the largest and best rated reinsurers will sometimes offer reinsurance layers on a 100%-only basis; both the price and the contract terms offered reflect the superior rating.

Offset clauses

At one time it was relatively common to see 'company-level' offset clauses. These allowed for offset of any balances due and agreed between the cedant and the reinsurer, irrespective of what contracts were involved. However on business currently being written typically offset clauses involving London Market reinsurers are at contract level only. This means that only balances due under the contract can be offset, for example a premium instalment offset against a claim payment. Clearly this offers very little RCCR protection to the cedant, particularly on medium or long tailed portfolios.

Collateralisation (pre and post loss, common methods)

One approach cedants take to allow use of reinsurers who would not otherwise be acceptable is collateralisation. No doubt we are all now familiar with the 'sidecar' arrangements whereby catastrophe reinsurance contracts have the limit fully collateralised, typically by a hedge fund. These contracts commonly have no reinstatement provisions (so-called 'one-shot' policies), and the reinsurer may not have requested any rating from the commercial rating agencies. Arguably we might expect the softening of rates to bring about the demise of such arrangements.

Cedants may also request that certain rated reinsurers put up some form of collateral either at outset or following an event with predetermined characteristics. This approach can often be seen where the cedant wishes to retain a specific reinsurer on its programme even though that reinsurer has been downgraded since the last renewal. Often the collateral is only in respect of ceded premium, and does not reflect the ceded limit.

Finally, reinsurance contracts may have clauses in place that require collateralisation if the reinsurer's rating drops below a predetermined limit; the next point covers this area.

Downgrade clauses

Downgrade clauses trigger pre-determined contractual changes in the event that the reinsurer has its credit rating reduced below a pre-set level, for example if their rating falls below A-.

The most common downgrade clauses allow the cedant to receive a pro-rata refund of the ceded premium for the unexpired risk element of the protection. Again this is a feature of more benefit to property portfolio protections than medium or long tailed portfolios.

An alternative downgrade clause will trigger collateralisation, but as described above the collateralisation may be only in respect of the ceded premium, not the exposed limit.

Commutation implications

If a cedant becomes concerned with either the ability of a reinsurer to pay claims, or its willingness to do so in a timely and efficient way, it may seek commutation of some or all of its contracts with that reinsurer. However in such circumstances the reinsurer might be quite aggressive in the commutation negotiations, requiring a commutation settlement significantly lower than the net present value of the expected recoveries and often giving no allowance for the benefit of removing such uncertain elements from its own balance sheet.

Typically, the perception of the level of distress will drive the level of discount that can be achieved. Discussion of further business practices used by run-off reinsurance companies to encourage commutation is outside the scope of this paper, but is an interesting area of research, particularly for anyone who is concerned that the reinsurance industry has lost its innovative edge.

Overall the impact is that the cedant might be prepared to accept significantly less than 100% of recoveries so that it can secure timely payment and relieve an administrative burden.

Recent developments – Credit wraps

During late 2006 / early 2007 we saw two high profile credit wraps; brief details of both are provided below.

It takes a lot of time and effort to engineer these new contracts from scratch. The concept of 'reinsurer default' sounds objective enough, but in practice it is very difficult to describe this in a legal contract to the satisfaction of buyers, sellers and their lawyers alike. Reinsurers and Banks can also have quite different views regarding appropriate risk transfer in such a protection as well, of course, as the price.

Furthermore, the investment banks are used to dealing with much larger transactions than most reinsurers would recognise so many potential buyers of credit protections on their own balance sheet simply won't be able to offer a big enough portfolio to attract sellers – some banks won't view it as being worth the effort. The list of potential bespoke transactions (like the Aspen deal) might therefore be quite small, although this hurdle should reduce each time a deal is done and the technology becomes more 'accepted'.

More general hedges against reinsurance market credit exposure (i.e. like that offered by the Merlin transaction) may be more tractable with sellers, but the degree of mismatch between the cover provided and the default exposures of the buyer can only be described as significant. As such this type of product also does not offer a complete solution to the problem.

We anticipate this will be an area of developing activity over the next couple of years as insurers seek to tie down more aspects of their balance sheet risk.

Aspen

November 2006 saw the first reinsurer default protection policy in the London market. The deal was brokered by R K Carvill & Co Ltd between the Bermudian reinsurer Aspen Insurance Holdings Ltd and the investment bank Deutsche Bank.

The transaction effectively involves an insurance policy from the bank to protect a portfolio of up to $420m of Aspen's reinsurance contracts against the risk of default due to inability to pay. The five year policy covers current and future receivables under existing policies and further reinsurance policies taken out through its term, and is triggered by "…certain non-standard credit events designed to isolate the specific nature of counterparty risk in the reinsurance market".

Whilst the concept of a credit wrap on reinsurance risks is very appealing, and indeed we might expect to see more of these, it is notable that this first transaction took a very large amount of development work to come to fruition. One of the key challenges was developing a workable payment trigger definition that satisfied the needs of both buyer and seller.

It is also important to note that this transaction covers only an inability to pay, not reinsurance disputes (i.e. refusal to pay). As such the protection offered by this transaction does not immunise Aspen from all reinsurance default risk.

Hannover Re (‘Merlin’)

In January 2007 Hannover Re, the German reinsurance group, announced its launch of the first synthetic sale of default risk among its peers and clients in a collateralised debt obligation arranged by Societe General, the French investment bank.

A synthetic collateralised debt obligation, or CDO, repackages a pool of credit derivatives into tranches of notes with varying risk profiles and coupon rates. These notes are then sold off to investors.

In the Merlin deal, the pool comprises Euros 1bn of underlying exposures from 100 different insurance and reinsurance companies, the majority of which are US-based - although it also includes some Lloyd's of London businesses and others from across Europe and Asia.

Merlin sold Euros 95m of floating-rate notes rated AAA to BBB against the pool of underlying credit exposures. The CDO will pay money from the investors to Hannover Re if more than six of these pool companies suffer bankruptcy, insolvency or an inability to pay its reinsurance debts. All Merlin investments will be wiped out if 16 of the companies included in the CDO defaults.

As with the Aspen deal, Merlin does not cover any disputed claims or unwillingness to pay. Another similarity with the Aspen deal is that Merlin avoids the issue of variable recovery rates post-default by fixing (in monetary terms) the payout associated with any default covered by the transaction.

APPENDIX F

SOME MORE THOUGHTS ON CORRELATIONS

Getting realistic interactions between each counterparty and your own company's risk profile must be the least well developed area of capital modelling, however it has potentially one of the greatest impacts within the capital model.

The problem, as always, is getting enough credible data from which to determine the type and magnitude of the dependency structure between two counterparties, or between a counterparty and your own company's gross loss experience. Once this information is available it is relatively straightforward to implement the relationship either analytically or by using simulation techniques.

In addition to considering whether X and Y are correlated, we should also think about whether the cause is some external factor Z. For example, consider an insurance company writing only property and professional indemnity in South Eastern USA.

- A major US hurricane, say $100bn market loss value, could cause significant gross losses to this insurer together with a substantial reinsurance recoverable.

- However, this same event could well have impaired the credit-worthiness of the reinsurers that protect the insurer.

- On the other hand, depending on the mix, a poor gross result in professional indemnity might create similar gross loss ratios but not translate into either reinsurance recoverables or impaired credit-worthiness of its reinsurers.

- The relationship between the gross loss ratio and the credit-worthiness of the reinsurers depends not only on the quantum of the gross loss ratio but also on the underlying cause of the high loss ratio.

One approach would be to correlate the distribution of gross claims with the likelihood or reinsurer default; however a more reliable approach might be to estimate the relationship of each of gross losses and reinsurer defaults with major market events. You can then directly model cause and effect ensuring that market events large enough to change reinsurer credit-worthiness are simultaneously causing the cedant's gross loss ratio and reinsurance recoverables to increase.

Consequently before considering correlations, we would recommend finding direct methods of modelling those elements which are more 'cause and effect'.

For items which appear to show an interdependency that cannot be modelled directly via the cause and effect route, we must consider some form of correlation modelling. However, before getting to the parameterising stage we need to think about what parts of the model should be correlated. There are many possibilities, but in practice compromises must be made to ensure that the model does not get too complex.

It can be dangerously misleading to develop a very complex model in those circumstances where there is a paucity of data upon which the modelling assumptions are based. Furthermore, the more items we are correlating, the greater the difficulty of having a positive definite correlation matrix without compromising on the individual coefficients of correlation. Getting the right balance between a theoretically complete model and one that has the flexibility to produce fast but insightful answers and which accurately reflects the most significant interdependencies is extremely important.

The key to this two stage approach is to consider the materiality of each of the relationships against the overhead of building them into your model. The list below is designed to stimulate ideas rather than provide a definitive set of relationships:

- Rates of default are correlated to historical earnings. When earnings are high, insurers build capital (and run-off business is likely to bring additional profit in coming years) and investment available. When earnings are poor...

- The probability of default across the entire reinsurance market increases following a major market shock. This can come from many sources e.g. hurricane, earthquake, tsunami, stock market crash, terrorism event, etc. These events may also cause a significant increase in the cedant's gross reserves and its reinsurance recoverables.

- The 'severity' of the impact of a default can also increase with such things as using the same panel of reinsurers year after year for long tail risks (note that often there is little choice about building this accumulation) and also by the inter-relationships between different companies.

- How will the other counterparties at the same security rating be affected if a counterparty defaults?

- Will counterparties in neighbouring security ratings also be affected?

- If default occurs, what percentage are you likely to receive and what will influence this amount?

- Delayed payments are inevitable in the event of insolvency. For example Trinity Insurance Company went into run-off in January 1992 and entered a scheme of arrangement (SoA) in March 1993. Trinity's amended SoA, which introduced a mechanism that allowed claims from creditors to be finalised and valued, became effective in mid-December 2003 and has only now ended. If this had been run as a traditional run-off, rather than a scheme of arrangement, the auditors believe that payouts would have taken even longer.

- If a counterparty is downgraded or put into run-off but is not technically insolvent, what does this mean in terms of delayed payments?

Once the relationships have been considered it is important to think about how they can be incorporated into the model. Some of the relationships may not fit into the current structure of the model, possibly due to previous modelling choices in other areas. If this happens consider the materiality of the relationship against the time taken to restructure the model and the possible implications to the existing parts of the model. It can also be helpful to reflect on the original purpose behind the model and whether the inclusion of more sophistication will add value or distract away from this purpose.

One relatively common way of correlating the counterparty default module to the rest of the DFA model is to pick a result that captures most of the relationships you consider material from the list above, for example gross incurred claims or the new recoverables in the modelled year. This assumes that if the insurer has a large loss the counterparty is likely also to be to be impacted. However, this approach misses out on the situations when a significant market wide loss occurs but has a relatively minor impact on the insured's gross incurred claims (or recoverables, as applicable).

An alternative approach is to model major market losses; for each of these major market losses one then simulates the following:

- The insured's gross incurred claim for the event;

- New credit ratings for each reinsurer (other than those in run-off). For example you might assume that in the event of a market loss of between $100bn and $150bn there would be a 20% chance of an AA-rated reinsurer retaining that rating, 35% chance on a 1 notch downgrade, 25% chance of a 2 notch downgrade, 10% chance of a 3 notch downgrade, etc;

- New credit ratings for any reinsurers in run-off, reflecting the dependency they may have on 'live' reinsurers. This is likely to be a smaller probability of downgrade compared to a live reinsurer at the same credit rating.

The simulation then proceeds as normal, but with the revised credit ratings for each reinsurer. This explicitly captures the relationship between major market losses, the insured's gross losses and reinsurance recoverables and the likelihood of reinsurer downgrade or default.

This approach would in theory require an assumed distribution of 'post event ratings' for each group of reinsurers with the same current credit rating for each major market loss. In practice it might be more practical to divide market losses into a small number of groups e.g. $50 – 100bn, $100 – 150bn, $150 – 200bn, exceeding $200bn.

Whatever approach is chosen the drawbacks should be understood and quantified, and if material included as an element of model risk to avoid understating the overall capital figures (obviously, common sense is also needed not to overestimate the capital associated with credit risk).

The best solution does not necessarily have to involve more complex DFA modelling. The weaknesses of a selected modelling approach can be covered elsewhere by targeted stress testing. For example, if 'modelled recovery before bad debt' is used to correlate with the counterparty then, as mentioned above, the link with wider market losses is lost. The adequacy of modelled capital could be separately tested against some scenarios that represent the 'lost' link.

Our illustrative Excel model shows one example of how one might model the impact of both major market losses and the underwriting cycle.

APPENDIX G

REFERENCES

Books and papers we found particularly useful and relevant include those below. We reviewed more than these so the list is not meant to be exhaustive, but these in particular are all worth a look.

Books

- 'Credit derivatives pricing models' by Schonbucher (2003), ISBN 0470842911
- 'Credit risk measurement' by Saunders and Allen (2002), ISBN 047121910X

Papers

- 'Reinsurance Bad Debt Provisions For General Insurance Companies' (2000, updated 2005) by Bulmer, Gallagher, Green, Hart, Matthews, Moss and Sheaf
- 'Best's Impairment Rate and Rating Transition Study – 1977 to 2006' (2007) by A M Best
- 'Bond Prices, Default Probabilities and Risk Premiums' (2005) by Hull, Predescu and White
- 'Modelling credit: Theory and practice' (2001) by O'Kane and Schlogl
- 'The Merton/KMV approach to pricing credit risk' (2001) by Sundaram
- 'Valuing credit default swaps I: No counterparty default risk' (2000) by Hull and White
- 'Credit risk modelling: Current practices and applications' (1999) by the Basle committee on banking supervision
- 'Assessment of target capital for general insurance firms' (2006) by Hitchcox, Hinder, Kaufman, Maynard, Smith and White

Websites

- http://www.defaultrisk.com/

APPENDIX H

SCREEN PRINTS FROM OUT ILLUSTRATIVE MODEL

2007 GIRO Working Party - Reinsurance Counterparty Credit Risks

Illustrative Model For Quantifying RCCR Exposures
Using "Default Intensity Curves" Based On
Capital Market Prices For Corporate Bonds and CDS's

For user instructions and general discussion please read the accompanying paper
"Reinsurance Counterparty Credit Risks - Practical Modelling Suggestions"
dated 27th July 2007, written by the 2007 RCCR GIRO Working Party (Flower et al)

We the authors do not invite reliance on, nor accept responsibility for, the information contained within this workbook nor in the accompanying paper. Further, we do not give any guarantee, undertaking or warranty concerning the accuracy, completeness or up-to-date nature of the information contained herein and do not accept responsibility for any loss which may arise from reliance on information in this workbook.

2007 GIRO Working Party - Reinsurance Counterparty Credit Risks
Illustrative Model Using Default Intensity Curves

REINSURANCE RECOVERABLES INPUT

Reinsurance counterparty buckets (with associated credit ratings)

1	Bucket 1	AA
2	Bucket 2	A
3	Bucket 3	NR

Unpaid reinsurance recoverables by underwriting year and bucket

	Bucket 1	Bucket 2	Bucket 3	Total
Prior	850	2,000	0	2,850
1999	200	1,000	0	1,200
2000	100	300	0	400
2001	0	0	250	250
2002	250	0	500	750
2003	300	250	150	700
2004	500	1,500	100	2,100
2005	300	500	0	800
2006	150	0	0	150
2007	800	0	0	800
All yrs	3,450	5,550	1,000	10,000

Recovery payment patterns assuming no default (annual from 1.1.07 by underwriting year)

	1	2	3	4	5	6	7	8	9	10
Prior	100.0%									
1999	50.0%	50.0%								
2000	33.3%	33.3%	33.3%							
2001	40.0%	20.0%	20.0%	20.0%						
2002	28.6%	28.6%	14.3%	14.3%	14.3%					
2003	30.0%	20.0%	20.0%	10.0%	10.0%	10.0%				
2004	28.6%	21.4%	14.3%	14.3%	7.1%	7.1%	7.1%			
2005	17.6%	23.5%	17.6%	11.8%	11.8%	5.9%	5.9%	5.9%		
2006	10.5%	15.8%	21.1%	15.8%	10.5%	10.5%	5.3%	5.3%	5.3%	
2007	5.0%	10.0%	15.0%	20.0%	15.0%	10.0%	10.0%	5.0%	5.0%	5.0%

Discount rate for NPV calculations

12.0% assumed cost of capital

Note that if your recoveries default you are effectively supporting this through other forms of capital (i.e. equity).

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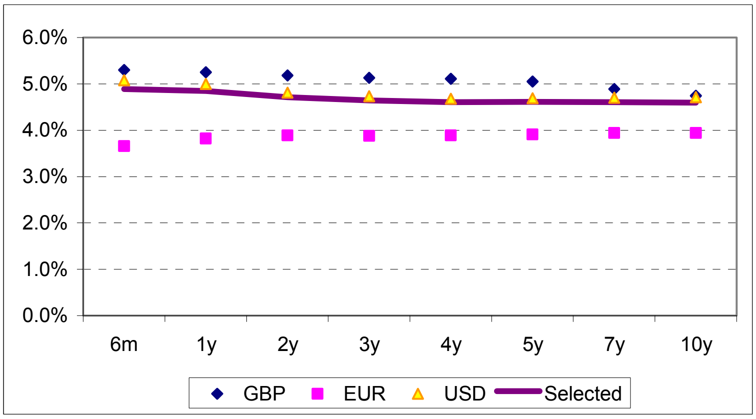
Illustrative Model Using Default Intensity Curves

DEFAULT-FREE YIELD CURVE SELECTION

Benchmark government bond yields				Weighted	Selected
			GBP	10%	
			EUR	15%	
			USD	75%	
	GBP	EUR	USD	Selected	Selected
6m	5.30%	3.66%	5.08%	4.89%	4.89%
1y	5.25%	3.82%	5.00%	4.85%	4.85%
2y	5.18%	3.89%	4.81%	4.71%	4.71%
3y	5.13%	3.88%	4.73%	4.64%	4.64%
4y	5.11%	3.89%	4.68%	4.60%	4.60%
5y	5.05%	3.91%	4.69%	4.61%	4.61%
7y	4.89%	3.94%	4.70%	4.61%	4.61%
10y	4.74%	3.94%	4.71%	4.60%	4.60%



2007 GIRO Working Party - Reinsurance Counterparty Credit Risks
Illustrative Model Using Default Intensity Curves

DEFAULT INTENSITY CURVE SELECTION

Bloomberg data: Illustrative CDS spreads (mid price, basis points = proxy for default rates) for example companies as at 29-Dec-06

Issuer: AIG
Comment: Data as at 29/12/06

	Quoted	Fitted
6m		2.70
1y	2.75	2.75
2y		3.80
3y	4.91	4.91
4y		7.50
5y	9.76	9.76
7y		13.00
10y		18.00

Issuer: QBE Insurance Grp
Comment: Data as at 29/12/06

	Quoted	Fitted
6m		5.00
1y	4.75	6.00
2y		7.00
3y	9.50	10.00
4y		12.00
5y	14.38	15.00
7y	20.75	20.00
10y	25.50	25.50

Issuer: XL Capital
Comment: Data as at 29/12/06

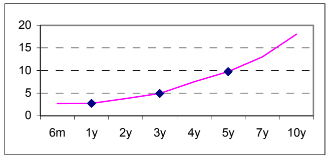
	Quoted	Fitted
6m		5.00
1y	5.07	5.00
2y		8.00
3y	9.57	10.00
4y		15.00
5y	20.29	20.00
7y		28.00
10y		40.00

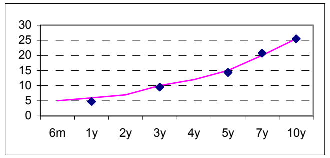
Issuer: Reference Credit D
Comment: BBB- rated

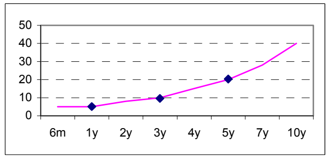
	Quoted	Fitted
6m	187.00	200.00
1y		200.00
2y		200.00
3y	210.00	205.00
4y		210.00
5y		215.00
7y		220.00
10y	225.00	225.00

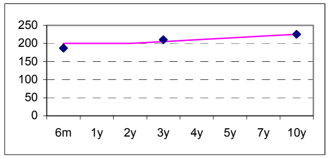
Issuer: Reference Credit E
Comment: Not rated

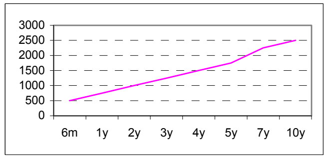
	Quoted	Fitted
6m		500.00
1y		750.00
2y		1000.00
3y		1250.00
4y		1500.00
5y		1750.00
7y		2250.00
10y		2500.00





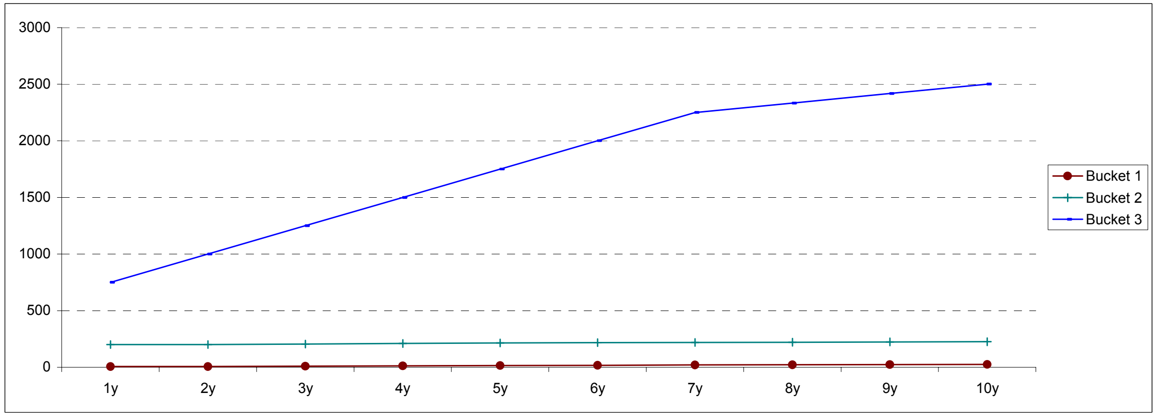






User-selected default intensity curves for use in RCCR model

	Bucket 1	Bucket 2	Bucket 3
1y	6.00	200.00	750.00
2y	7.00	200.00	1000.00
3y	10.00	205.00	1250.00
4y	12.00	210.00	1500.00
5y	15.00	215.00	1750.00
6y	17.50	217.50	2000.00
7y	20.00	220.00	2250.00
8y	21.82	221.65	2332.50
9y	23.69	223.35	2417.50
10y	25.50	225.00	2500.00



Assumed recovery rates and lags on default

		Bucket 1	Bucket 2	Bucket 3
Recovery	Mean	0.60	0.50	0.45
	Stochastic	0.60	0.50	0.45
Lag (yrs)	Mean	3.00	3.00	5.00
	Stochastic	3.00	3.00	5.00

2007 GIRO Working Party - Reinsurance Counterparty Credit Risks
Illustrative Model Using Default Intensity Curves

DEPENDENCIES

Massive catastrophe event?

10y Probability :	10.0%	*100 yr return period*	Boosts all default probabilities by a scaling factor of	5	
Does it happen?	0		plus an additive factor of	5.0%	
In which year?	5		For a period of	3	years

Cycle bottoming out leading to a period of increased strain on reinsurers reserves?

10y Probability :	90.0%	Boosts all default probabilities by a scaling factor of	2	
Expected in which year?	3	plus an additive factor of	1.0%	
Does it happen?	1	For a period of	3	years
Happens in which year?	3			

2007 GIRO Working Party - Reinsurance Counterparty Credit Risks
Illustrative Model Using Default Intensity Curves

DEFAULT SIMULATION MODEL - Bucket 1

Bucket 1

Expected future payments

	Total	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Prior	850	850	0	0	0	0	0	0	0	0	0
1999	200	100	100	0	0	0	0	0	0	0	0
2000	100	33	33	33	0	0	0	0	0	0	0
2001	0	0	0	0	0	0	0	0	0	0	0
2002	250	71	71	36	36	36	0	0	0	0	0
2003	300	90	60	60	30	30	30	0	0	0	0
2004	500	143	107	71	71	36	36	36	0	0	0
2005	300	53	71	53	35	35	18	18	18	0	0
2006	150	16	24	32	24	16	16	8	8	8	0
2007	800	40	80	120	160	120	80	80	40	40	40
	3,450	**1,396**	**546**	**405**	**356**	**273**	**179**	**141**	**66**	**48**	**40**

Inferred default probabilities

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Default spread	0.06%	0.07%	0.10%	0.12%	0.15%	0.18%	0.20%	0.22%	0.24%	0.26%
Default free yields	4.85%	4.71%	4.64%	4.60%	4.61%	4.61%	4.61%	4.60%	4.60%	4.60%
Defaultable yields	4.91%	4.78%	4.74%	4.72%	4.76%	4.78%	4.81%	4.82%	4.84%	4.85%
ZCB Default free	0.9538	0.9121	0.8727	0.8352	0.7983	0.7632	0.7297	0.6977	0.6671	0.6380
ZCB Defaultable	0.9532	0.9109	0.8702	0.8314	0.7926	0.7556	0.7200	0.6862	0.6537	0.6226
Survival probability	0.9994	0.9987	0.9971	0.9954	0.9929	0.9900	0.9867	0.9835	0.9798	0.9759
Cond'l survival prob.	0.9994	0.9992	0.9985	0.9983	0.9974	0.9971	0.9967	0.9967	0.9963	0.9960
Cond'l default prob.	0.06%	0.08%	0.15%	0.17%	0.26%	0.29%	0.33%	0.33%	0.37%	0.40%

Default Simulation

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Prop cat effect	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Cycle effects	0.00%	0.00%	1.15%	1.17%	1.26%	0.00%	0.00%	0.00%	0.00%	0.00%
Adjusted def prob.	0.06%	0.08%	1.31%	1.34%	1.52%	0.29%	0.33%	0.33%	0.37%	0.40%
Default trigger	0	0	0	0	0	0	0	0	0	0
Default state	0	0	0	0	0	0	0	0	0	0
Recovery rate	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Recovery Lag	0	0	0	0	0	0	0	0	0	0

Recovery calculation

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Due	3,450	1,396	546	405	356	273	179	141	66	48	40
Receive	3,450	1,396	546	405	356	273	179	141	66	48	40
Discount	12.0%	0.945	0.844	0.753	0.673	0.601	0.536	0.479	0.427	0.382	0.341
D't w/lag	12.0%	0.945	0.844	0.753	0.673	0.601	0.536	0.479	0.427	0.382	0.341
NPV Due	2,712	1,319	461	305	240	164	96	68	28	18	14
NPV Get	2,712	1,319	461	305	240	164	96	68	28	18	14

Note that any recovery lag is allowed for above in the 'Discount' factor.

2007 GIRO Working Party - Reinsurance Counterparty Credit Risks
Illustrative Model Using Default Intensity Curves

DEFAULT SIMULATION MODEL - Bucket 2

Bucket 2

Expected future payments

	Total	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Prior	2,000	2,000	0	0	0	0	0	0	0	0	0
1999	1,000	500	500	0	0	0	0	0	0	0	0
2000	300	100	100	100	0	0	0	0	0	0	0
2001	0	0	0	0	0	0	0	0	0	0	0
2002	0	0	0	0	0	0	0	0	0	0	0
2003	250	75	50	50	25	25	25	0	0	0	0
2004	1,500	429	321	214	214	107	107	107	0	0	0
2005	500	88	118	88	59	59	29	29	29	0	0
2006	0	0	0	0	0	0	0	0	0	0	0
2007	0	0	0	0	0	0	0	0	0	0	0
	5,550	**3,192**	**1,089**	**453**	**298**	**191**	**162**	**137**	**29**	**0**	**0**

Inferred default probabilities

	1	2	3	4	5	6	7	8	9	10
Default spread	2.00%	2.00%	2.05%	2.10%	2.15%	2.18%	2.20%	2.22%	2.23%	2.25%
Default free yields	4.85%	4.71%	4.64%	4.60%	4.61%	4.61%	4.61%	4.60%	4.60%	4.60%
Defaultable yields	6.85%	6.71%	6.69%	6.70%	6.76%	6.78%	6.81%	6.82%	6.83%	6.85%
ZCB Default free	0.9538	0.9121	0.8727	0.8352	0.7983	0.7632	0.7297	0.6977	0.6671	0.6380
ZCB Defaultable	0.9359	0.8782	0.8234	0.7714	0.7211	0.6745	0.6308	0.5899	0.5516	0.5157
Survival probability	0.9813	0.9629	0.9435	0.9236	0.9033	0.8838	0.8644	0.8456	0.8268	0.8083
Cond'l survival prob.	0.9813	0.9812	0.9798	0.9789	0.9780	0.9785	0.9780	0.9782	0.9778	0.9776
Cond'l default prob.	1.87%	1.88%	2.02%	2.11%	2.20%	2.15%	2.20%	2.18%	2.22%	2.24%

Default Simulation

	1	2	3	4	5	6	7	8	9	10
Prop cat effect	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Cycle effects	0.00%	0.00%	1.15%	1.17%	1.26%	0.00%	0.00%	0.00%	0.00%	0.00%
Adjusted def prob.	1.87%	1.88%	3.17%	3.28%	3.45%	2.15%	2.20%	2.18%	2.22%	2.24%
Default trigger	0	0	0	0	0	0	0	0	0	0
Default state	0	0	0	0	0	0	0	0	0	0
Recovery rate	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Recovery Lag	0	0	0	0	0	0	0	0	0	0

Recovery calculation

		1	2	3	4	5	6	7	8	9	10
Due	5,550	3,192	1,089	453	298	191	162	137	29	0	0
Receive	5,550	3,192	1,089	453	298	191	162	137	29	0	0
Discount	12.0%	0.945	0.844	0.753	0.673	0.601	0.536	0.479	0.427	0.382	0.341
D't w/lag	12.0%	0.945	0.844	0.753	0.673	0.601	0.536	0.479	0.427	0.382	0.341
NPV Due	4,755	3,016	919	341	200	115	87	65	13	0	0
NPV Get	4,755	3,016	919	341	200	115	87	65	13	0	0

Note that any recovery lag is allowed for above in the 'Discount' factor.

2007 GIRO Working Party - Reinsurance Counterparty Credit Risks
Illustrative Model Using Default Intensity Curves

DEFAULT SIMULATION MODEL - Bucket 3

Bucket 3

Expected future payments

	Total	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Prior	0	0	0	0	0	0	0	0	0	0	0
1999	0	0	0	0	0	0	0	0	0	0	0
2000	0	0	0	0	0	0	0	0	0	0	0
2001	250	100	50	50	50	0	0	0	0	0	0
2002	500	143	143	71	71	71	0	0	0	0	0
2003	150	45	30	30	15	15	15	0	0	0	0
2004	100	29	21	14	14	7	7	7	0	0	0
2005	0	0	0	0	0	0	0	0	0	0	0
2006	0	0	0	0	0	0	0	0	0	0	0
2007	0	0	0	0	0	0	0	0	0	0	0
	1,000	**316**	**244**	**166**	**151**	**94**	**22**	**7**	**0**	**0**	**0**

Inferred default probabilities

	1	2	3	4	5	6	7	8	9	10
Default spread	7.50%	10.00%	12.50%	15.00%	17.50%	20.00%	22.50%	23.33%	24.18%	25.00%
Default free yields	4.85%	4.71%	4.64%	4.60%	4.61%	4.61%	4.61%	4.60%	4.60%	4.60%
Defaultable yields	12.35%	14.71%	17.14%	19.60%	22.11%	24.61%	27.11%	27.93%	28.77%	29.60%
ZCB Default free	0.9538	0.9121	0.8727	0.8352	0.7983	0.7632	0.7297	0.6977	0.6671	0.6380
ZCB Defaultable	0.8901	0.7600	0.6221	0.4887	0.3684	0.2671	0.1866	0.1394	0.1027	0.0748
Survival probability	0.9332	0.8332	0.7128	0.5851	0.4614	0.3500	0.2557	0.1998	0.1539	0.1173
Cond'l survival prob.	0.9332	0.8928	0.8555	0.8208	0.7887	0.7586	0.7305	0.7814	0.7703	0.7620
Cond'l default prob.	6.68%	10.72%	14.45%	17.92%	21.13%	24.14%	26.95%	21.86%	22.97%	23.80%

Default Simulation

	1	2	3	4	5	6	7	8	9	10
Prop cat effect	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Cycle effects	0.00%	0.00%	1.15%	1.17%	1.26%	0.00%	0.00%	0.00%	0.00%	0.00%
Adjusted def prob.	6.68%	10.72%	15.61%	19.09%	22.39%	24.14%	26.95%	21.86%	22.97%	23.80%
Default trigger	0	0	0	0	0	0	0	0	0	0
Default state	0	0	0	0	0	0	0	0	0	0
Recovery rate	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Recovery Lag	0	0	0	0	0	0	0	0	0	0

Recovery calculation

		1	2	3	4	5	6	7	8	9	10
Due	1,000	316	244	166	151	94	22	7	0	0	0
Receive	1,000	316	244	166	151	94	22	7	0	0	0
Discount	12.0%	0.945	0.844	0.753	0.673	0.601	0.536	0.479	0.427	0.382	0.341
D't w/lag	12.0%	0.945	0.844	0.753	0.673	0.601	0.536	0.479	0.427	0.382	0.341
NPV Due	803	299	206	125	101	56	12	3	0	0	0
NPV Get	803	299	206	125	101	56	12	3	0	0	0

Note that any recovery lag is allowed for above in the 'Discount' factor.

2007 GIRO Working Party - Reinsurance Counterparty Credit Risks
Illustrative Model Using Default Intensity Curves

DEFAULT SIMULATION MODEL - TOTAL PORTFOLIO

TOTAL PORTFOLIO

Expected future payments - Before credit risk

	Total	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Prior	2,850	2,850	0	0	0	0	0	0	0	0	0
1999	1,200	600	600	0	0	0	0	0	0	0	0
2000	400	133	133	133	0	0	0	0	0	0	0
2001	250	100	50	50	50	0	0	0	0	0	0
2002	750	214	214	107	107	107	0	0	0	0	0
2003	700	210	140	140	70	70	70	0	0	0	0
2004	2,100	600	450	300	300	150	150	150	0	0	0
2005	800	141	188	141	94	94	47	47	47	0	0
2006	150	16	24	32	24	16	16	8	8	8	0
2007	800	40	80	120	160	120	80	80	40	40	40
	10,000	**4,905**	**1,880**	**1,023**	**805**	**557**	**363**	**285**	**95**	**48**	**40**

Expected future payments - Allowing for credit risk

		1	2	3	4	5	6	7	8	9	10
Due	10,000	4,905	1,880	1,023	805	557	363	285	95	48	40
Receive	10,000	4,905	1,880	1,023	805	557	363	285	95	48	40
Default'd	0	0	0	0	0	0	0	0	0	0	0
NPV Due	8,270	4,634	1,586	771	541	335	195	136	41	18	14
NPV Get	8,270	4,634	1,586	771	541	335	195	136	41	18	14
NPV Lost	0	0	0	0	0	0	0	0	0	0	0

Provision = expected value of this cell

NPV Ratio Lost Recoveries 0% *This is the proportion of the NPV of recoveries that you lose through defaults*

2007 GIRO Working Party - Reinsurance Counterparty Credit Risks
Illustrative Model Using Default Intensity Curves

CASHFLOW STRAIN

Expected future payments before credit risk = Reinsurers share of the gross losses as they are settled

Total	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
10,000	4,905	1,880	1,023	805	557	363	285	95	48	40

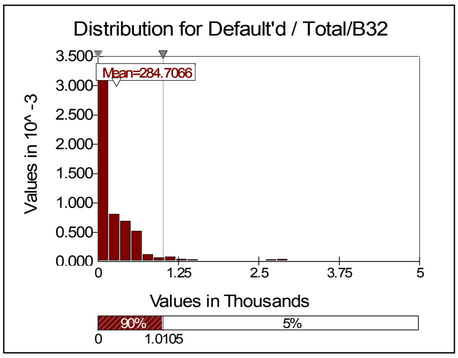
Reinsurance recoveries actually made, as they are received

	Total	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Bucket 1																
Recovery	3,450	1,396	546	405	356	273	179	141	66	48	40					
Delay		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cashflow	3,450	1,396	546	405	356	273	179	141	66	48	40	0	0	0	0	0
Bucket 2																
Recovery	5,550	3,192	1,089	453	298	191	162	137	29	0	0					
Delay		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cashflow	5,550	3,192	1,089	453	298	191	162	137	29	0	0	0	0	0	0	0
Bucket 3																
Recovery	1,000	316	244	166	151	94	22	7	0	0	0					
Delay		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cashflow	1,000	316	244	166	151	94	22	7	0	0	0	0	0	0	0	0
	Total	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
	10,000	4,905	1,880	1,023	805	557	363	285	95	48	40	0	0	0	0	0

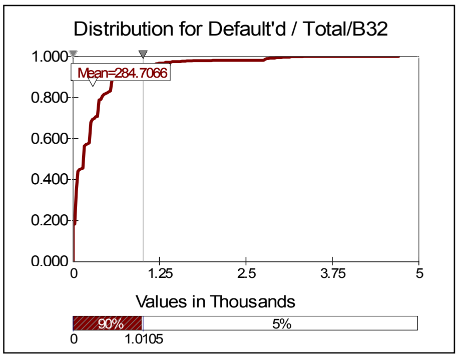
Cashflow strain

	Total	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Outflow	10,000	4,905	1,880	1,023	805	557	363	285	95	48	40	0	0	0	0	0
Inflow	10,000	4,905	1,880	1,023	805	557	363	285	95	48	40	0	0	0	0	0
Strain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cumulative		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Peak	0															

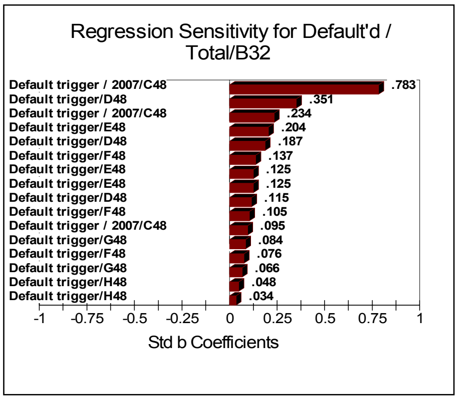
Simulation Results for
Default'd / Total / B32



Summary Information	
Workbook Name	lustrative RCCR Model.xl
Number of Simulations	1
Number of Iterations	100,000
Number of Inputs	40
Number of Outputs	24
Sampling Type	Latin Hypercube
Simulation Start Time	26/07/2007 10:03
Simulation Stop Time	26/07/2007 10:06
Simulation Duration	00:02:59
Random Seed	1103590267



Summary Statistics					
Statistic	**Value**	**%tile**	**Value**		
Minimum	0	5%	0	19.0%	1
Maximum	4,705	10%	0		
Mean	285	15%	0	Mean	285
Std Dev	474	20%	4	69.5%	285
Variance	224476.0831	25%	4		
Skewness	3.823246854	30%	16	95.0%	1,011
Kurtosis	20.94960012	35%	68	97.5%	1,479
Median	150	40%	68	99.0%	2,843
Mode	0	45%	87	99.5%	3,017
Left X	0	50%	150	99.9%	3,325
Left P	5%	55%	150		
Right X	1,011	60%	242		
Right P	95%	65%	242		
Diff X	1,011	70%	314		
Diff P	90%	75%	376		
#Errors	0	80%	408		
Filter Min		85%	550		
Filter Max		90%	635		
#Filtered	0	95%	1,011		



Sensitivity			
Rank	**Name**	**Regr**	**Corr**
#1	Default trigger /	0.783	0.239
#2	Default trigger /	0.351	0.250
#3	Default trigger /	0.234	0.353
#4	Default trigger /	0.204	0.257
#5	Default trigger /	0.187	0.361
#6	Default trigger /	0.137	0.236
#7	Default trigger /	0.125	0.154
#8	Default trigger /	0.125	0.309
#9	Default trigger /	0.115	0.111
#10	Default trigger /	0.105	0.156
#11	Default trigger /	0.095	0.057
#12	Default trigger /	0.084	0.179
#13	Default trigger /	0.076	0.232
#14	Default trigger /	0.066	0.117
#15	Default trigger /	0.048	0.119
#16	Default trigger /	0.034	0.073

2007 GIRO Working Party - Reinsurance Counterparty Credit Risks
Illustrative Model Using Default Intensity Curves

COMPARE WITH A TRADITONAL DETERMINISTIC CALCULATION

Unpaid reinsurance recoverables by underwriting year and bucket

	Bucket 1	Bucket 2	Bucket 3	Total
Prior	850	2,000	0	2,850
1999	200	1,000	0	1,200
2000	100	300	0	400
2001	0	0	250	250
2002	250	0	500	750
2003	300	250	150	700
2004	500	1,500	100	2,100
2005	300	500	0	800
2006	150	0	0	150
2007	800	0	0	800
All yrs	3,450	5,550	1,000	10,000

Factor selection based on corporate bond defaults table - Used Moody's 5 year for illustration purposes

	Moodys	Select
AAA	0.19%	0.19%
AA	0.78%	0.78%
A	1.22%	1.22%
BBB	3.40%	3.40%
BB	9.93%	9.93%
B	23.80%	23.80%
CCC	40.50%	40.50%
NR		50.00%

	Rating	Default	Exposure	Recover	Reserve
Bucket 1	AA	0.8%	3,450	60%	11
Bucket 2	A	1.2%	5,550	50%	34
Bucket 3	NR	50.0%	1,000	45%	275
		3.2%	10,000		320

Statistics based on our model

Probability of a loss greater than zero:	19%	
Mean loss (reserve with no prudency margin):	285	
Various percentile losses of possible interest:	95.0%	1,011
	97.5%	1,479
	99.0%	2,843
	99.5%	3,017
	99.9%	3,325
Expected Proportion of Recoveries lost	2.8%	
Expected Proportion of NPV Recoveries lost	3.2%	
"Compounding impact" of delays on defaults	1.121	
Mean 'economic' loss (with no prudency margin):	319