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PwC Solvency II Life Insurers' Risk Capital Survey

Summary Report

PwC's risk capital survey covers the data and methodologies adopted by firms in determining risk capital under Solvency II, as well as the resulting risk calibrations. This survey considers Internal Model and Standard Formula life insurance companies in the UK.

October 2015

pwc

Participants

We would like to express our thanks to the following firms who took part in our survey:

Admin Re UK
AEGON UK
AVIVA UK Life
Legal & General Group Plc
Lloyds Banking Group Plc
Liverpool Victoria Friendly Society Limited
Phoenix Life
Prudential UK
Royal London Mutual Insurance Society Limited
Standard Life Assurance Limited

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1. Introduction

I am delighted to present the findings of our 2015 Life Insurers' Solvency II Risk Capital Survey.

Drawing on information from 10 UK companies, the key focus of the survey is the capital evaluation of material risks.

The report aims to help your business compare its methodologies and assumptions with others in the market. This can provide valuable insights at a time when many insurers are in debate with their regulators over Internal Model approval, and are thinking through market disclosures of risks.

The survey covers a diverse range of UK participants– the majority of which are using an Internal Model or Partial Internal Model and the remainder using the Standard Formula. Where a risk sits under the Standard Formula, or outside a Partial Internal Model, we have asked for the calibration methodology and results to be from the Pillar 2 Economic Capital Model used by the participant. We use the term "Internal Model" interchangeably for these results, and those from a Partial or Full Internal Model in course of application to the regulator.

Our thanks go to the firms who took part for kindly sharing their time and their insights (please see the participants page for the full list). I hope you find the report useful, and we look forward to engaging in discussions with you about the themes emerging.

Regards,

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Director, PwC

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Purpose and use of this report

This report has been prepared to be shared with the public. We accept no liability (including for negligence) to you or anyone else in connection with this report. The report should be read in its entirety; reading individual sections in isolation may result in misinterpretation. The report contains information obtained or derived from interviews conducted with survey participants. We have not sought to establish the reliability of all of those sources of information or otherwise verify the information so provided. Accordingly no representation or warranty of any kind (whether express or implied) is given by PwC to any person as to the accuracy or completeness of the report.

This report is a summary of the detailed PwC survey which covers the data and methodologies adopted by firms in determining risk capital under Solvency II, as well as the resulting risk calibrations. The survey considers Internal Model and Standard Formula life insurance companies in the UK. Participants have received a more detailed version of this report, however the key messages summarised in here are consistent with the detailed report.

In some areas, not all 10 participants responded to the questions asked. This will have been for various reasons, for example where participants employ the Standard Formula calibrations to calculate a risk under their Economic Capital Model; where the question is not relevant to the participant's business, etc. In these instances, the total number of responses will be less than 10; however we have ensured that results disclosed in this report are always from a sufficiently credible set of responses. Where we have received an insufficient number of responses to meet this objective, we have refrained from disclosing results.

Compliance with TAS requirements

The Financial Reporting Council ('FRC') requires actuaries to comply with Technical Actuarial Standards ('TASs') for various types of actuarial work. We also believe that it is normally appropriate to apply the requirements of the TASs to other work conducted by actuaries. Given the nature of the work, however, we have not attempted to follow the requirements of the TASs on this assignment. You will need to consider the impact of this limitation on your interpretation of our work and results.

Materiality

We have defined materiality as a capital component that is above 5% of the total diversified SCR. This definition is applied consistently throughout the report.

2. Material risk exposure

In this section we have summarised the key themes emerging from the results provided by our participants.

Credit, equity, longevity, persistency and operational risks remain the highest individual contributors to participants' undiversified and diversified Solvency Capital Requirement ("SCR"). This survey concentrates on these risks, and the all important aggregation of all risks.

For a more detailed discussion of individual risk sub-modules and calibration results, please see the separate risk sections which follow.

Result highlights

Persistency risk

- Persistency has traditionally been a major risk for most lines of business under Individual Capital Assessment (ICA). However, Solvency II brings short contract boundaries for many pure savings contracts which dampens the impact of persistency stress for the SCR, though not for the business.
- Persistency risk sees a far greater variety in practical application of stresses than many other risks. This wide diversity indicates participants have diverse views on how to recognise and thus manage this risk. Insurers will need to ensure PRA appreciates the areas of comparative complexity and caution within their models.

Longevity risk

- There is general consensus that male longevity is impacted more heavily than the equivalent female assumptions by a 1-in-200 shock to longevity base risk.
- The average longevity trend stress has strengthened when compared to our 2014 survey for both males and females.

Equity risk

- There are a wide range of calibration models adopted by participants, however the industry continues to arrive at a fairly narrow range of stresses across the 1-in-10, 1-in-50 and 1-in-200 levels.

Credit risk

- The majority of participants model credit spread risk separately to transition and default risk, however there is little consensus between these participants on calibration methodology for transition and default risk.
- Following explicit PRA guidance regarding 'gilt swap spread risk', the majority of participants stress spreads on sovereign debt.
- All participants who have applied for a matching adjustment make an allowance for the portion of the increase in credit spread that feeds through to an increase in the assumed matching adjustment, there is less consensus how the size of this allowance compares to current ICA approaches.

Operational risk

- The wider Financial Services industry has seen a preference steadily emerging for modelling frequency risk using Poisson distributions and severity risk using Lognormal distributions. The same picture is being seen in our survey results.

Aggregation

- Firms typically use a Gaussian copula or a variance-covariance matrix as their overarching aggregation method and so allow for dependency in stress by moving the entire correlation matrix to stress levels.
- Firms anticipate higher diversification from their life risks than from their market risks, in line with our previous surveys.

3. Life insurance risk

In this section, we consider what have proved to be the more important non market risks for life insurers, namely longevity and persistency.

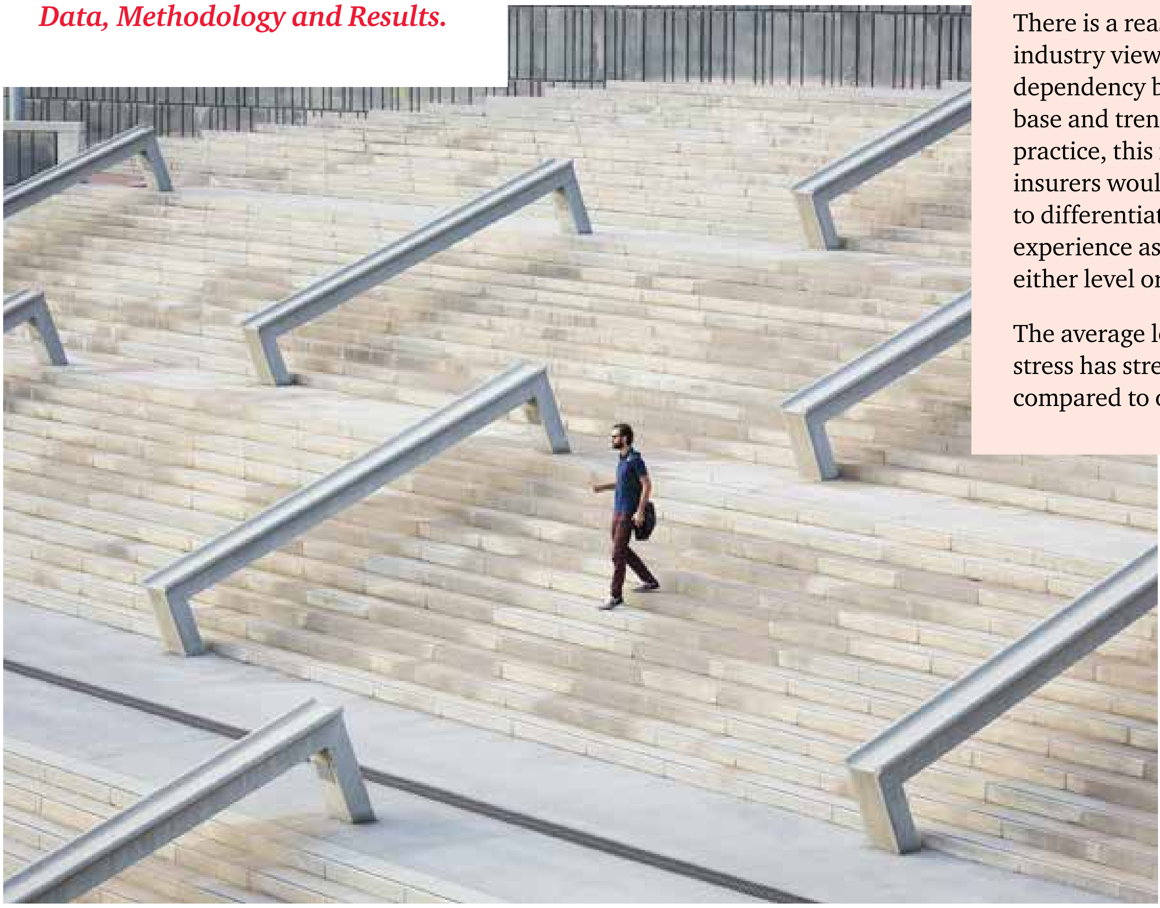
For each of these risks, we asked participants for a range of quantitative and qualitative information on their risk calibrations as applied in their Internal Model.

For each risk, the results have been grouped into Risk exposure, Data, Methodology and Results.

Longevity risk

Introduction

Solvency II defines longevity risk as the risk of loss, or of adverse change in the value of insurance liabilities, resulting from changes in the level, trend, or volatility of mortality rates, where a decrease in the mortality rates leads to an increase in the value of the insurance liabilities. It affects contracts where benefits are based on the likelihood of survival, i.e. annuities, pensions, pure endowments and specific types of health contract.



Most participants have opted for a two-risk-factor modelling approach, i.e. base and trend, with a wide variety of methods and results disclosed for the trend risk factor.

There is general consensus that male longevity is impacted more heavily than the equivalent female assumptions by a 1-in-200 shock to longevity base risk.

There is a reasonably uniform industry view that the level of dependency between longevity base and trend risks is low. In practice, this may indicate that insurers would find it difficult to differentiate emerging experience as being driven by either level or trend risk.

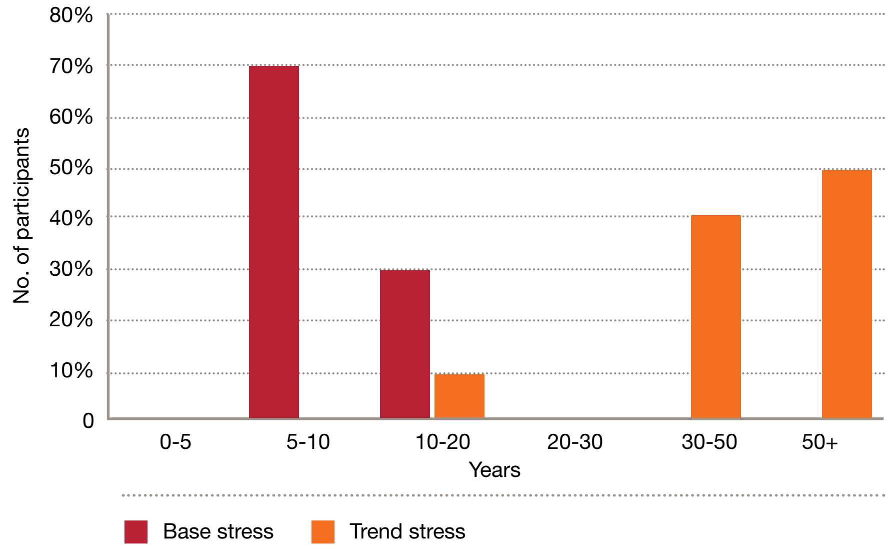
The average longevity trend stress has strengthened when compared to our 2014 survey.

Data

There is a general consensus within the industry with regards to data sources used for modelling longevity stress. The majority of participants indicated that they rely on own historic data when calibrating longevity base stresses, whilst data from the Office of National Statistics ("ONS") is used by most to calibrate trend stresses.

Figure 3.1 shows the data periods used for modelling longevity base and trend risks. The results are in line with the expectation that external data sources used in the calibration of trend risk are typically of a longer duration than internal experience data used for base risk.

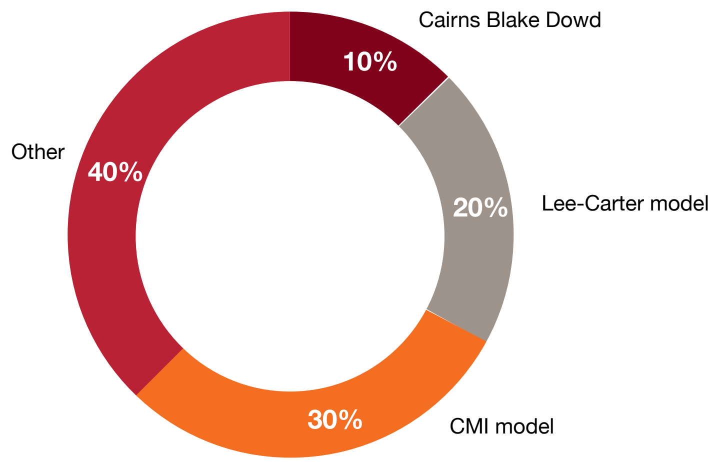
Figure 3.1: Data period used by survey participants in calibrating longevity risk stresses.



Methodology

There is general consensus amongst participants to fit a Normal distribution for the longevity base stress calibration. However there is little consensus on the best approach for modelling longevity trend stress. Figure 3.2 shows the proportion of participants that use the models available. Responses captured within 'Other' include Plat (extended) and internally developed stochastic model.

Figure 3.2: Distribution of modelling methodology used by survey participants in determining longevity trend risk stresses.



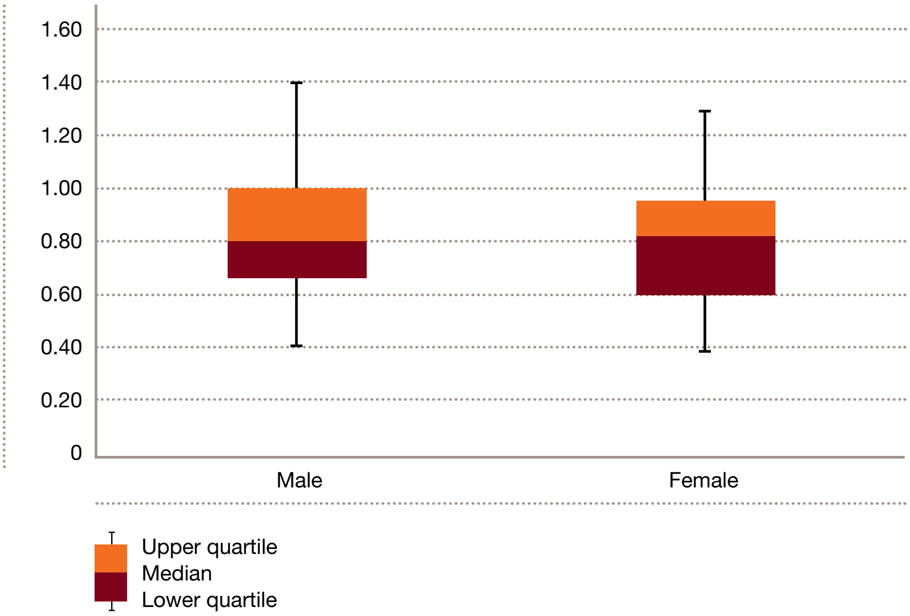
Results

Figure 3.3 and 3.4 outline participants' approaches to their longevity base and trend risk calibrations, as applied to immediate annuities on a 1-in-200 levels.

Notably, the average trend stress is consistently higher that the average base stresses at all levels.

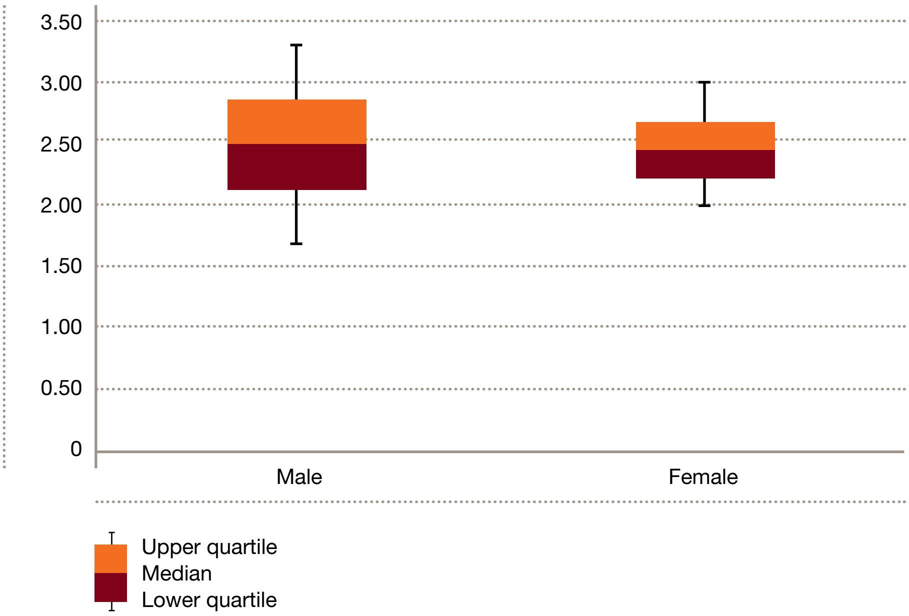
For longevity base, the majority of participants indicated the male stress is higher than the female with a minority applying the same stresses to male and female lives. There is general consensus that male longevity would be impacted more heavily than the equivalent female assumptions by a 1-in-200 shock to longevity base risk.

Figure 3.3: Distribution of calibrated Longevity base stresses for male and female lives expressed as a change in future life expectancy for a life currently aged 65 exact, measured in years.



The results for trend risk are less convergent, with an equal split between participants who consider the male trend stress to be more onerous than the female and vice versa.

Figure 3.4: Distribution of calibrated Longevity trend stresses for male and female lives expressed as a change in future life expectancy for a life currently aged 65 exact, measured in years.



Persistency risk

Solvency II defines persistency risk as the risk of loss, or of adverse change in the value of insurance liabilities, resulting from changes in the level or volatility of the rates of policy lapses, terminations, renewals and surrenders.

Persistency has traditionally been a major risk for most lines of business under ICA. However, Solvency II brings short contract boundaries for many pure savings contracts which dampens the impact of persistency stress.

Persistency risk sees a far greater variety in practical application than many other risks. This means that the survey results should be treated with some care when making comparisons between companies.

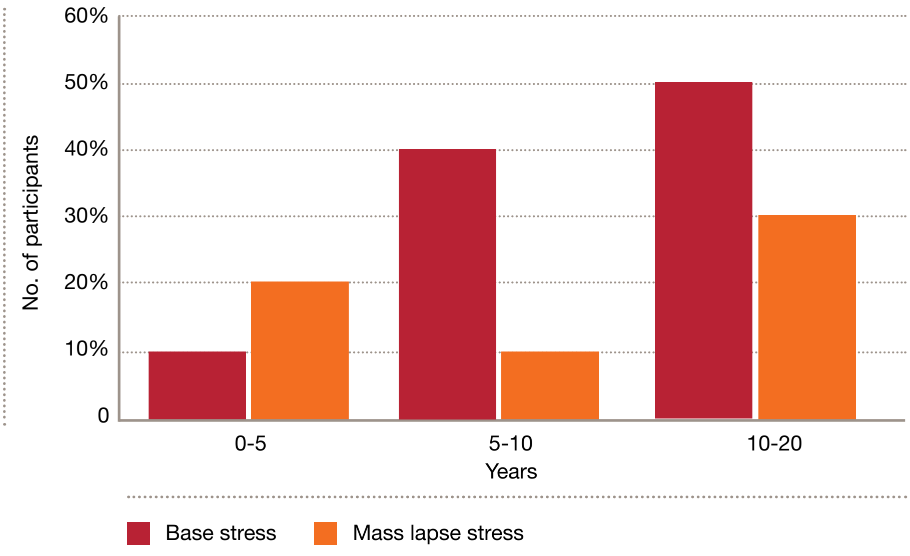
While the scale of both level and mass exit stresses see some grouping the choice of the correlation between these two aspects of persistency risk shows wide dispersion. The resultant capital held for persistency risk overall is likely to be very dependent on this assumption.

Data

The majority of participants rely on internal historic data when calibrating persistency level risk. In contrast, mass lapse stress calibrations relied more heavily on expert judgement, with some use of industry benchmarking. These approaches are reflected in the distribution of data periods considered when calibrating these stresses, which is detailed in Figure 3.5.

There is little consensus on the data period used for either the base or mass lapse persistency stresses. For the base stress a move towards longer periods is understandable from a credibility point of view, however, data quality may be a challenge for insurers using primarily historic experience – data may suffer from heterogeneity and accessibility issues. For the mass lapse stress, the lack of a longer term view may limit the robustness of participants' stress calibration.

Figure 3.5: Data period used by survey participants in the calibration of persistency stresses.



Methodology

Half the participants include all voluntary discontinuance decrements as a single risk driver in their persistency risk. The remainder do not model PUPs in the persistency stress calibration or model PUPs/partial withdrawals as a separate risk factor

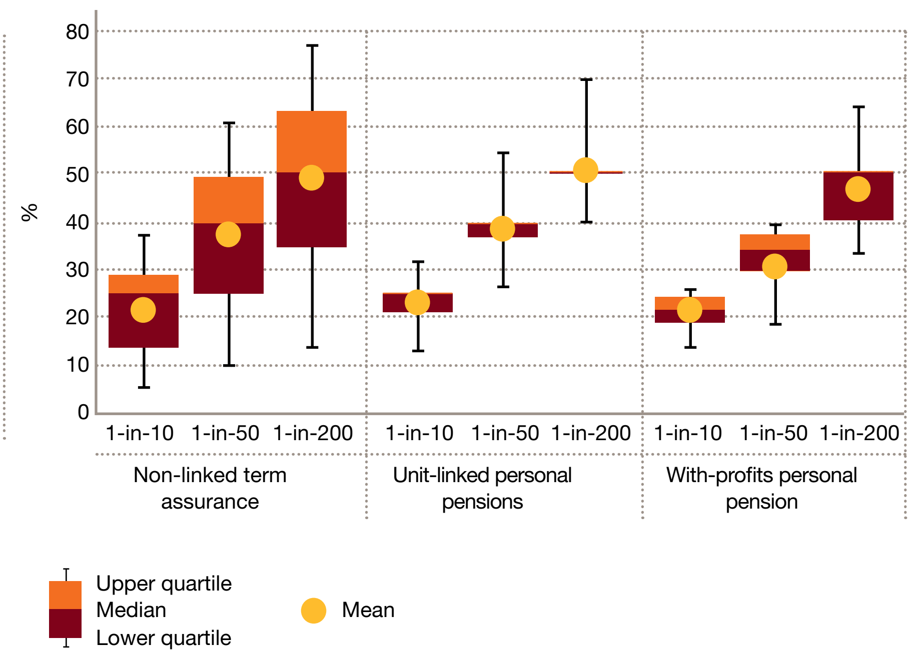
The majority of participants use the same approach to data extraction across different product groups however this still results in differences in stresses due to different experience data between product groups.

There was little consensus whether to apply stress policies differently dependent upon whether they gave a profit or loss on lapse. Opinion is also divided as to whether to apply durational persistency stresses and whether to differentiate stresses between books of policies open or closed to new business.

Persistency risk sees a far greater variety in practical application of stresses than many other risks. This wide diversity indicates participants have diverse views on how to recognise and thus manage this risk. Insurers will need to ensure PRA appreciates the areas of comparative complexity and caution within their models.

Results

Figure 3.6: Distribution of calibrated persistency base test at the 1-in-200, 1-in-50 and 1-in-10 significance levels.



4. Market risk

Solvency II states that the market risk module shall reflect the risk arising from the level or volatility of market prices of financial instruments which have an impact upon the value of the assets and liabilities of the undertaking. It shall properly reflect the structural mismatch between assets and liabilities, in particular with respect to duration.

In this section, we consider the following sub-modules of market risk:

- *Credit spread*
- *Credit transition and default*
- *Equity.*

For each risk sub-module, we asked participants for a range of quantitative and qualitative information on their risk calibrations as applied in their SII Internal Model. Should firms opt to model the relevant risk using the Standard Formula under SII, they were asked to provide responses as applicable to their Economic Capital Model (e.g. ICA). For each risk, the results have been grouped into Risk exposure, Data, Methodology and Results.

Credit spread risk

Solvency II defines spread risk as the risk arising from the sensitivity of the values of assets, liabilities and financial instruments to changes in the level or in the volatility of credit spreads over the risk-free interest rate term structure.

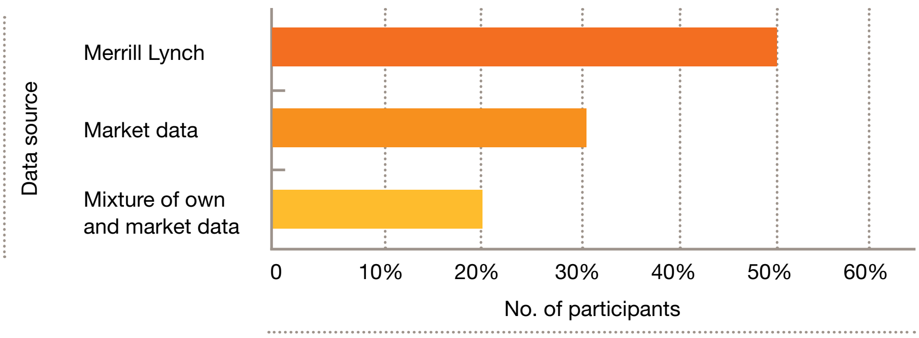
- The majority of participants model credit spread risk separately to transition and default risk.
- The survey reveals some grouping of calibrated stresses from participants, especially for 10 year terms and high rated bonds. Participants are however producing some marked differences in results which is perhaps unsurprising given the wide variety of methodologies and data sources being used. Lower rated bonds in particular display a diverse range of stresses.
- Following explicit PRA guidance regarding 'gilt swap spread risk', the majority of participants stress spreads on sovereign debt.
- All participants who have applied for a matching adjustment make an allowance for the portion of the increase in credit spread that feeds through to an increase in the assumed matching adjustment, however we note there is little consensus as to the size of this allowance.

Data

We asked participants about the source of data used to calibrate spread risk, illustrated in Figure 4.1.

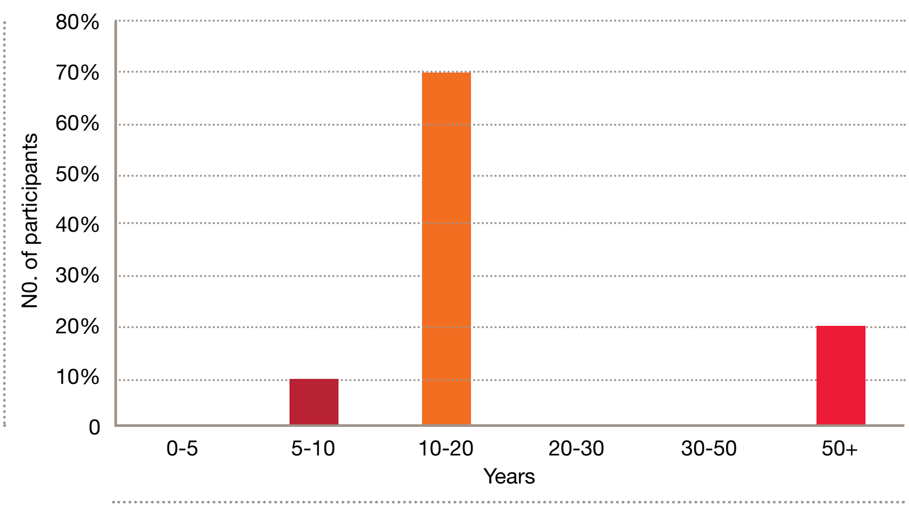
As in previous years, the majority of participants have cited Merrill Lynch as a key data source for the credit spread risk calibration, including participants using a variety of market data sources or a mixture of their own internal data and market data.

Figure 4.1: Data sources used by survey participants for the calibration of credit spread base stresses.



The popularity of this data source dictates the period from which historical data is to be examined. As we can see in Figure 4.2, the majority of participants use data from a 10 – 20 year historical period, corresponding with the choice of the Merrill Lynch dataset.

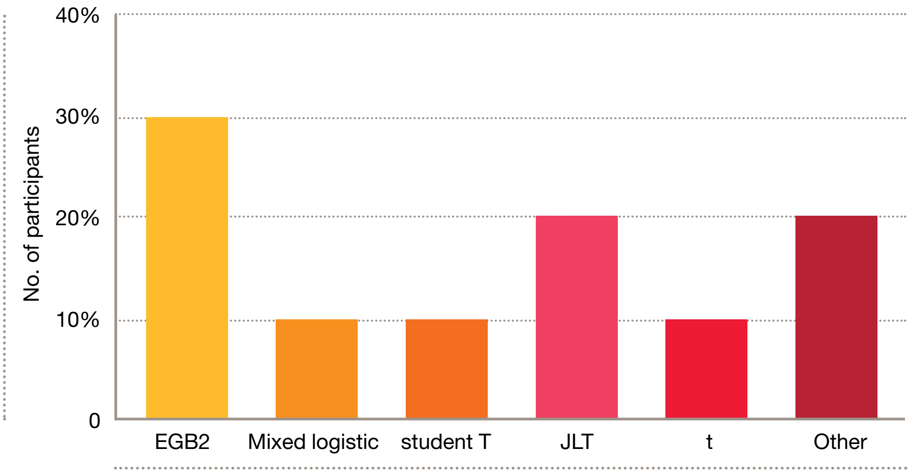
Figure 4.2: Data period used by survey participants for the calibration of credit spread stresses.



Methodology

Figure 4.3 shows the range of modelling methodologies used by survey participants to model credit spread stresses, demonstrating the lack of any industry consensus. Again, this is to be expected as firms tailor the methodology to best reflect their underlying risk exposure. Participants also indicated some differences over the granularity of credit spread modelling with the majority indicating that they segregate calibration by asset type. Examples include splitting between financial and non-financial assets and by currency.

Figure 4.3: Distribution of modelling methodology used by survey participants to calibrate credit spread stresses.



Results

We asked participants for details of the resulting calibrated stresses, split by financials and non-financials. The results can be seen in Figures 4.4 to 4.5.

The detailed results show that the average calibrated stress for financials is consistently higher than that for non-financials across all terms and ratings, as observed in 2014.

Figure 4.4: Calibrated basis point yield increase for credit spread by credit rating for financial corporate bonds. (1 -in-200)

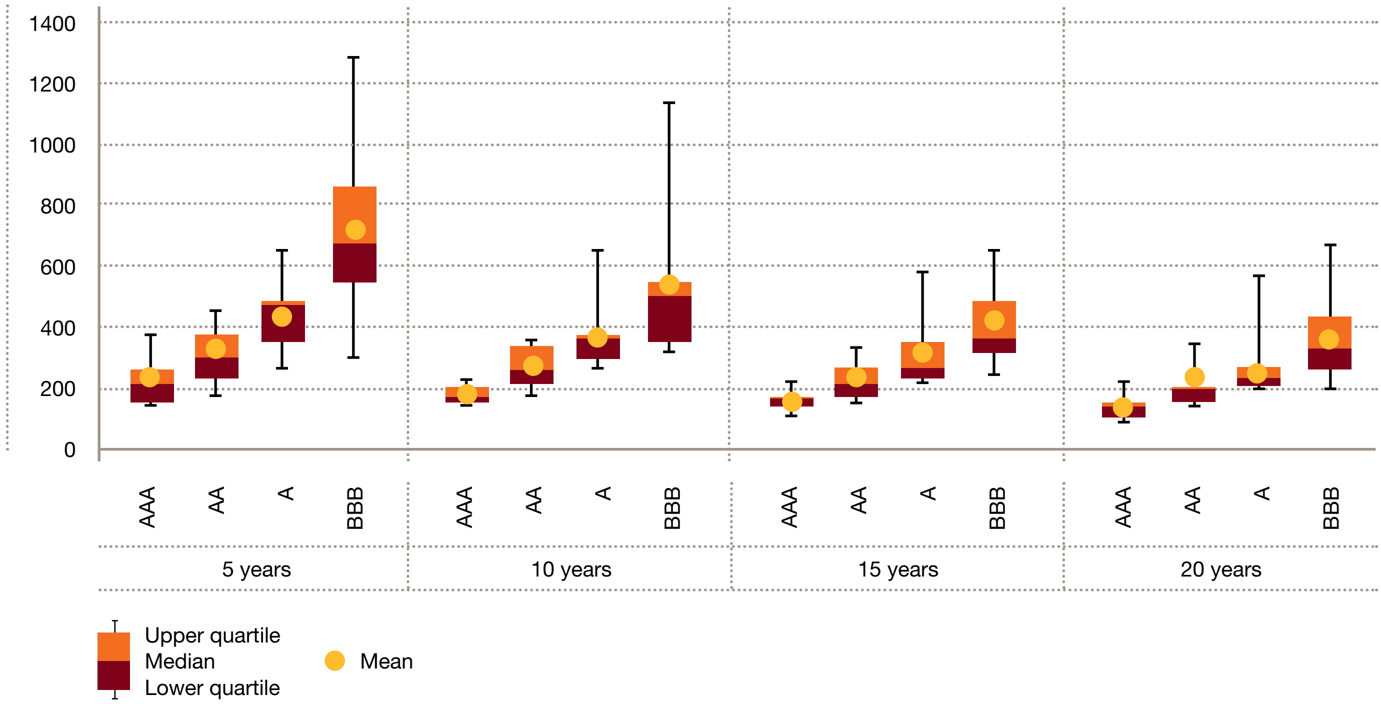
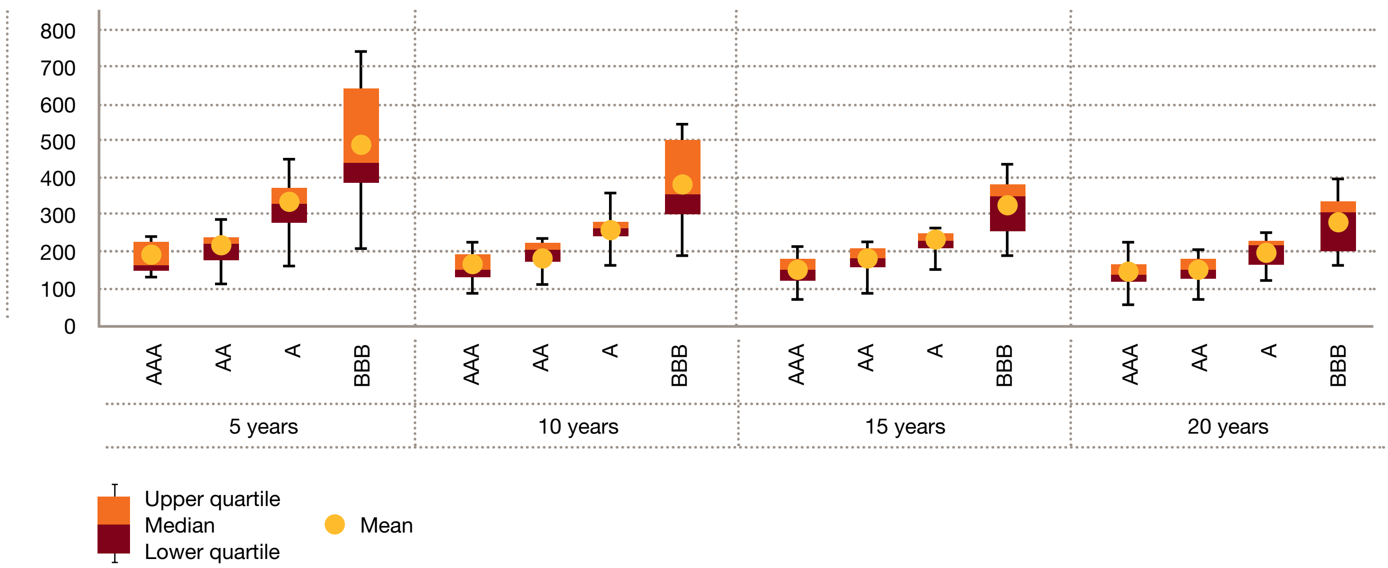


Figure 4.5: Calibrated basis point yield increase for credit spread by credit rating for non-financial corporate bonds. (1 -in-200)



Credit transition and default risk

Losses can also arise from the sensitivity of the values of asset and liabilities to changes in market assessments of the risk of future migration and/or default. Historically insurers have focussed on modelling credit risk holistically, focussing on spread changes to reflect movements in total return/value. The introduction of the matching adjustment calculation and associated split of transition and default risk from spread risk, combined with regulatory pressure, has led to a number of insurers choosing to reflect spread, transition and default elements separately within their modelling.

The majority of participants indicated that transition and default is modelled separately to credit spread risk in their internal model.

- All participants who model credit transition and default separately to spread risk use Moody's data to set their transition and default risk calibration.
- There is little consensus on calibration methodology amongst participants who model transition and default risk separately to spread risk.

Data

We asked participants about the source of data used to calibrate credit transition and default risk. All participants who model credit transition and default separately to spread risk use rating agency data (specifically Moody's) to set their transition and default risk calibration. This contrasts to the variety of market data sources used in the case of spread risk. We note that geographical differences are likely to arise from the use of Moody's data, if this consists of more readily available US data. Insurers will therefore need to make sure that the data used is appropriate for their particular exposures.

There is little consensus between participants on the length of data used to calibrate the credit transition and default stress, ranging from 10-20 years to more than 50 years. The shorter time periods indicated by some participants ensures consistency with the time period used to calibrate credit spread risk.

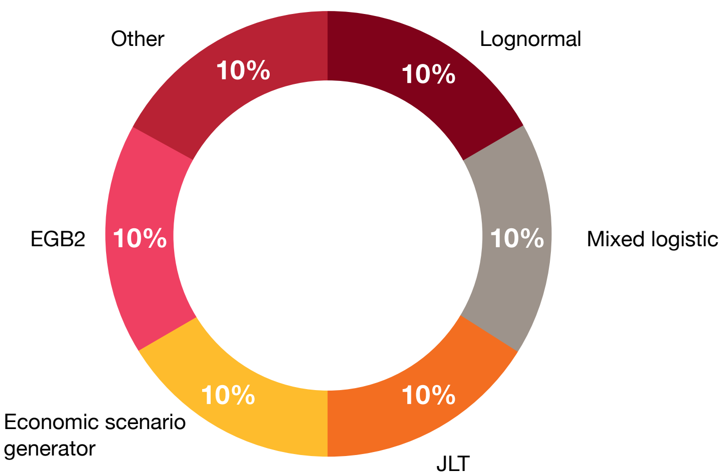
Methodology

Figure 4.6 shows the models used by participants to calibrate credit transition and default risk. The results show that there is little consensus on calibration methodology among those participants who model transition and default separately to credit spread risk.

The majority of participants who calibrate transition and default separately to credit spread risk indicated that the cost of transition within their internal model represents an average over a period of time (i.e. a "through the cycle" approach) rather than if it is driven by modelled stressed spreads at the point of transition (i.e. a "point in time" approach).

There is a general consensus amongst the participants who calibrate transition and default separately to credit spread risk that recovery rates within their internal model represent an average over a period of time rather than modelled dynamically at the point of default.

Figure 4.6: Distribution of modelling methodologies used by survey participants when calibrating transition and default stresses



Results

We asked participants for details of their calibrated stresses for credit transition and default, however due to the low number of responses we are unable to present the results.

Interaction between credit risk and the matching adjustment

The matching adjustment calculation reflects the yield over and above the risk free rate earned on an insurer's asset portfolio, less the fundamental spread in respect of transition and default risk. In this section we consider the interaction between credit risk (including both spread and transition and default) and the matching adjustment.

PRA feedback to the industry on matching adjustment applications has made clear that they expect an Internal Model to avoid a "mechanical" calculation that does not allow for stressed conditions to cause EIOPA to revisit its calculation of the fundamental spread. Separately EIOPA's current approach to calculating and publishing the fundamental spread has so far been based on a cost of downgrade that is insensitive to current market spread differentials but these "RC factors" are under review. However, there is still a lack of consensus across the industry on modelling approaches to accommodate all of these issues.

All participants who have applied for a matching adjustment make an allowance for the portion of the increase in credit spread that feeds through to an increase in the assumed matching adjustment, there is less consensus how the size of this allowance compares to current ICA approaches.

We asked participants if EIOPA's derivation of the cost of downgrade became more driven by current spread differentials what impact this would have on capital. The results are summarised in Figure 4.7.

We expect those participants with an SCR calculation that would remain broadly unchanged even if EIOPA moved its current method to a dynamic calculation (which responded to market spreads) may revisit their approach in future. (i.e. to avoid a fundamental spread that increases materially as spreads widen being double counted in the capital still being held for such spread impacts.)

All participants allow for the potential for EIOPA to revisit the calculation of the fundamental spread in future stressed conditions, with a minority only making an implicit allowance, i.e. allowing only a fixed percentage of increases in spread comes through the fundamental spread.

Participants responses are varied as to the reduction in mitigation resulting from the modelling of the matching adjustment compared to the ICA treatment of credit stress being offset by a reduction in technical provisions. The results are summarised in Figure 4.8.

Figure 4.7: Impact on participant's capital if EIOPA's derivation of the cost of downgrade became more driven by current spread differentials

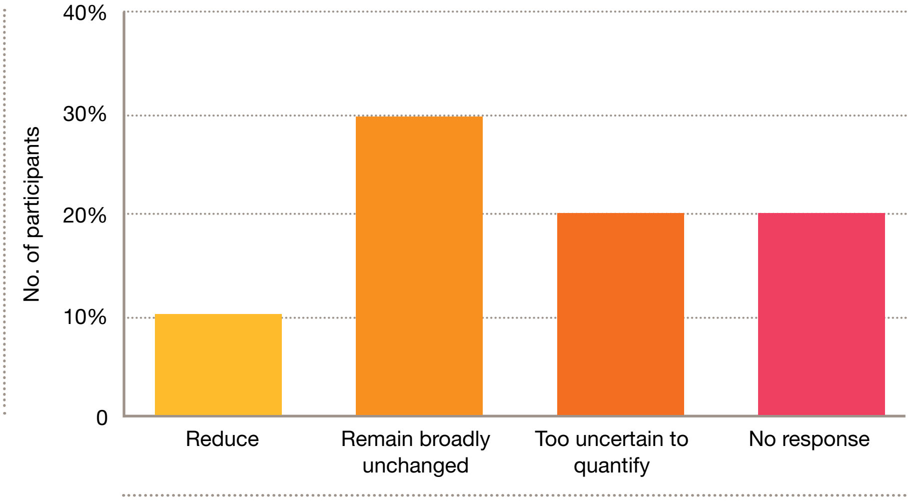
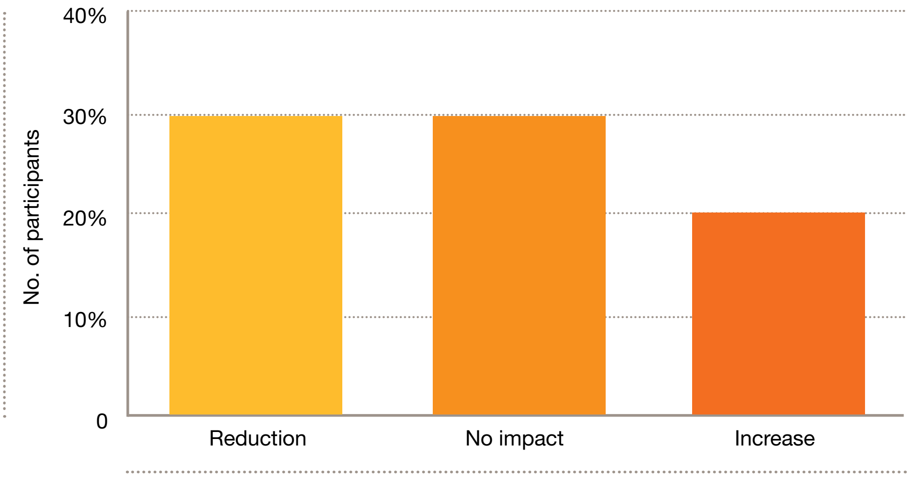


Figure 4.8: Mitigation impact from modelling of matching adjustment compared with ICA treatment of credit stress being offset by a reduction in technical provisions



Equity risk

Solvency II defines equity risk as that arising from the sensitivity of the values of assets, liabilities and financial instruments to changes in the level or in the volatility of market prices of equities.

There are a wide range of calibration models adopted by our participants, however the industry continues to arrive at a fairly narrow range of stresses across the 1-in-10, 1-in-50 and 1-in-200 levels.

The majority of participants (6/10) make an adjustment to the equity level stress calibration for basis risk, but only 1 participant adjusts the volatility stress calibration for basis risk between index data and its own portfolio.

Data

Survey participants indicated a broad range of data sources used in the calibration of equity level and volatility stresses. The responses are detailed in Figure 4.9. For level stresses, a range of market data sources were indicated, with Bloomberg and Morgan Stanley Capital International ("MSCI") proving the most popular.

For equity volatility stress, 'Other' sources refer to externally sourced bank data such as Morgan Stanley, Bank of America Merrill Lynch, Deutsche Bank, RBS, Barclays and Markit-Totem.

Figure 4.10 shows the corresponding spread of data periods used by industry participants. We note that participants tend to favour longer historical data periods when calibrating their equity risk level stresses. Shorter data periods are more typical for volatility calibration, which may point to a lack of credible data for equity volatility, notably at longer durations.

Figure 4.9: Data sources used by survey participants when calibrating equity level and volatility risk stresses

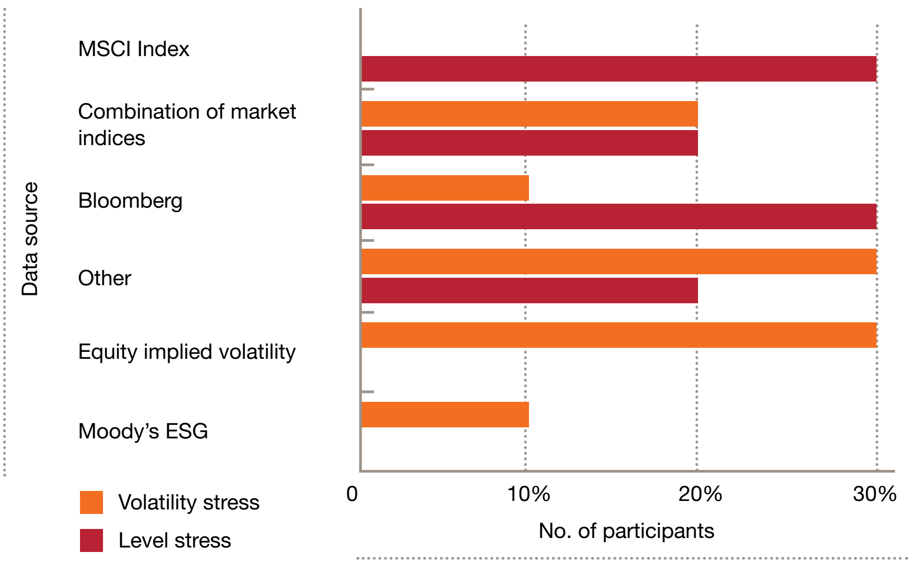
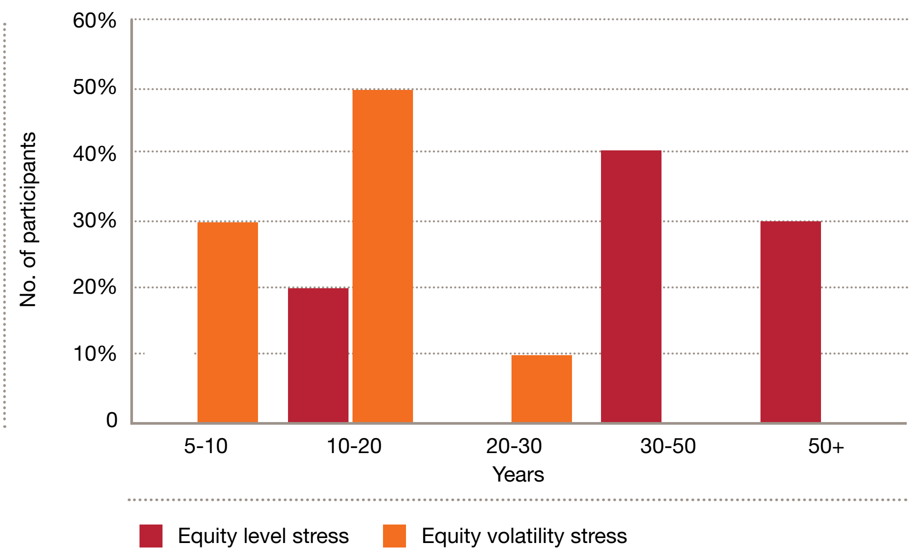


Figure 4.10: Data calibration for equity level and volatility risk



Methodology

In Figures 4.11 and 4.12 we have summarised the modelling methodology that our participants use when calibrating level and volatility stresses for equity risk. There is a lack of consensus amongst respondents – these are shown in the “Other” category.

Results

We asked participants to provide their calibrated stresses for equity risk at the 1-in-200, 1-in-50 and 1-in-10 significance levels. Figure 4.12 shows the resulting level stresses expressed as downward level stresses.

A particularly noteworthy aspect of these results is the very narrow range of derived stresses across participants, seemingly at odds with the variation in methodology we have discussed earlier. This demonstrates that despite the varying calibration approaches, the industry tends to conform to broadly similar resulting stresses.

Figure 4.11: Models used by participants in calibrating equity risk stresses.

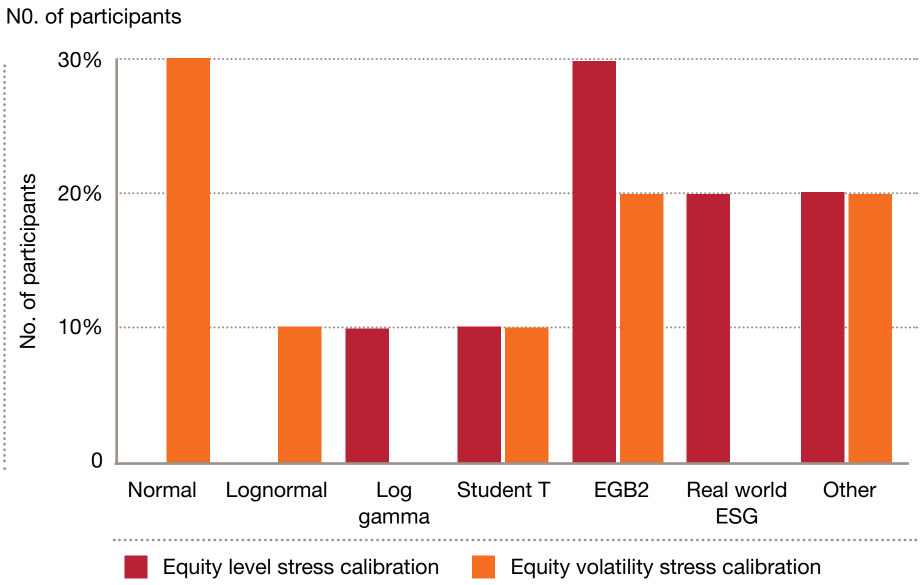
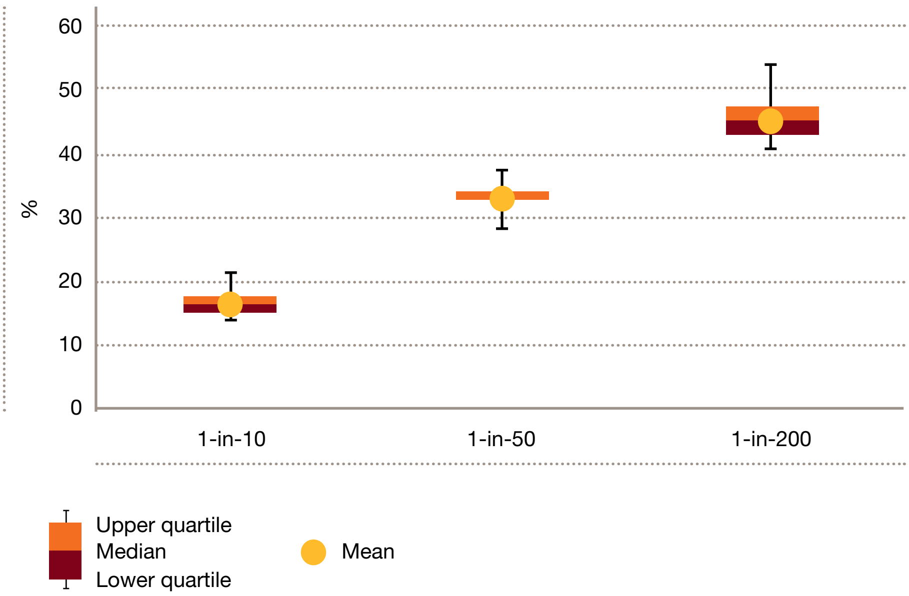


Figure 4.12: Distribution of calibrated 1-in-200, 1-in-50 and 1-in-10 equity level stresses.



5. Operational risk

Solvency II defines operational risk as the risk of loss arising from inadequate or failed internal processes, people and systems, or from external events (including legal risk).

Operational risk is a less material component of the SCR than insurance or market risk for participants. However, its underlying data is far less robust than other risks meaning it is more challenging to support through an Internal Model process. So while previous surveys have indicated modelled operational risk capital is usually higher than that delivered by the Standard Formula, this is an area where internal model applicants may yet default to using the Standard Formula calibration.

Modelling across the wider Financial Services industry has seen a preference emerging for modelling frequency risk using Poisson distributions and severity risk using Lognormal distributions.

Most participants agree that casual rationalisation is the main driver of dependencies between scenarios/ operational risk events.

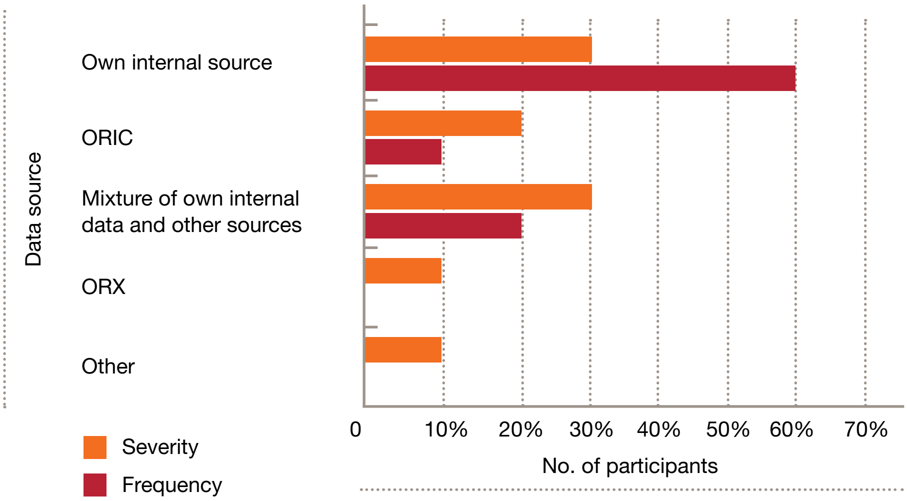
Data

Most participants rely on their internal sources to develop the loss scenarios used to support the calibration of the operational risk model.

Due to the relative immaturity of underlying data when compared to many market or life risks, one of the key challenges faced in modelling operational risk is the use of external data, in particular for the severity stress. As such, many participants use a mixture of internal data supported by some external data. The main sources of data used by participants to calibrate frequency and severity risks are as captured in Figure 5.1 below.

The periods of historical data used by respondents to calibrate frequency and severity risks are lower than would typically be used to model other risks, consistent with the challenges of limited data described above. Most participants use 5- 10 years of historical data.

Figure 5.1: Data sources used to determine frequency and severity risk stresses



Methodology

Modelling across the wider Financial Services industry has seen a trend emerging for modelling frequency risk using Poisson and severity risk using Lognormal distributions. As in our 2014 survey, the results in insurance reflect this trend. However, we note that while Lognormal remains a favoured distribution for modelling severity risk stresses, there is less consensus than for modelling of frequency risk, with Pareto also commonly used for frequency.

We also asked participants if they vary the severity distribution according to the type of scenario. Almost half the participants indicate that they do, with common approaches including varying the distribution depending on expected size and/or frequency of loss.

Modelled Scenarios

We asked survey participants to share the number of modelled scenarios used as an input in their operational risk model. There is still variation in the number of scenarios being modelled, but the majority of participants reported using 10 – 26 scenarios.

Clearly there needs to be sufficient scenarios to support the eventual derivation of a credible statistical representation of the risk, a probability density function(pdf) of the risk (the most common output of this scenario work).

Scenario modelling usually samples from the discrete categories that operational risk events are being grouped into. Almost half the participants indicated they allocated operational risk into 8-10 categories and majority of the remaining participants use 10-20 categories.

6. Risk aggregation

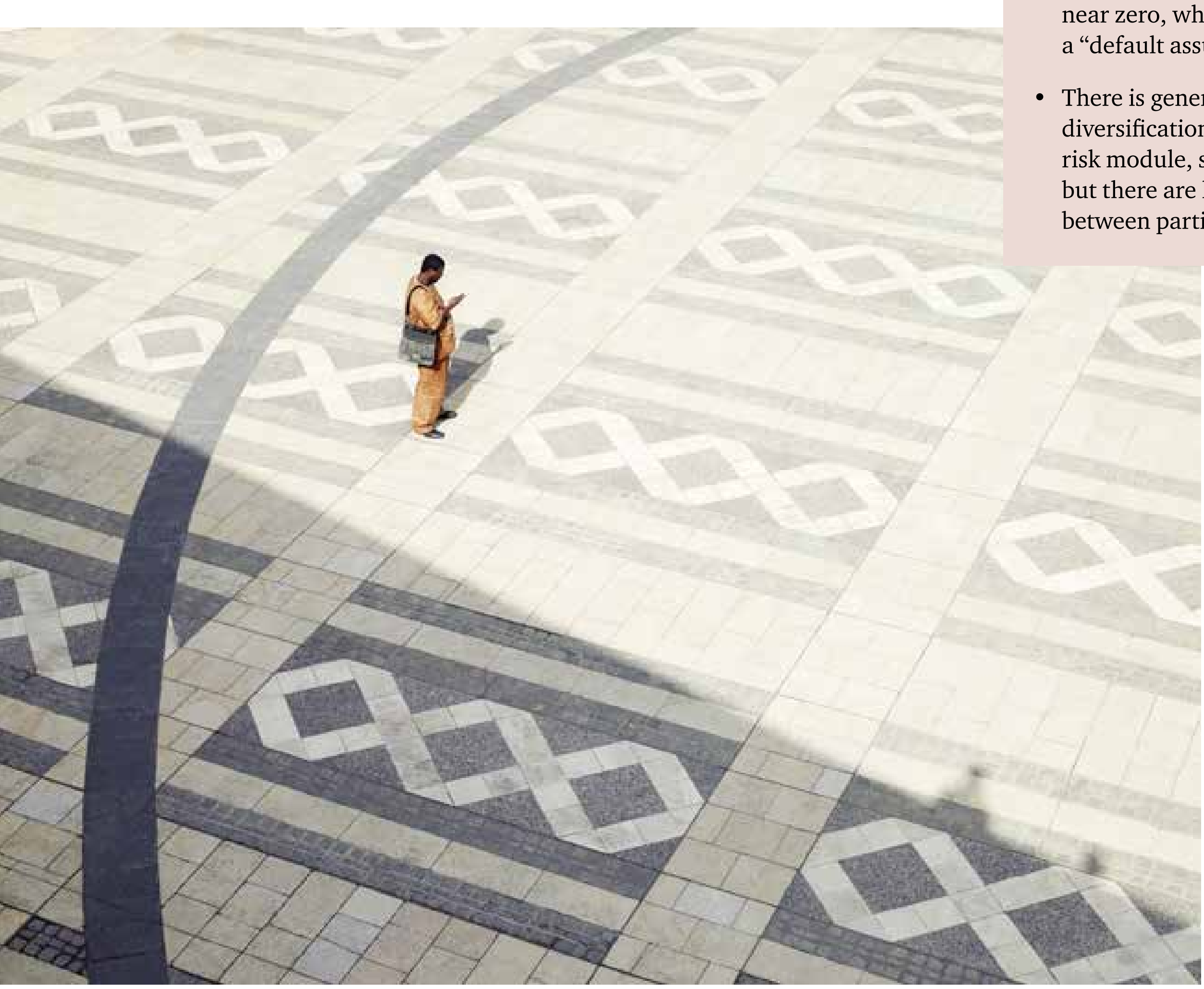
This section considers the approaches participants use in aggregating their individual risk modules to determine the total SCR, including the resulting diversification benefit realised.

We considered aggregation approaches for the following risk modules:

- *Life insurance risk*
- *Market risk*

We asked participants for a range of information on their aggregation models; the results have been grouped into Data and Methodology, Dependencies, Diversification Benefit.

- Firms typically use Gaussian copula or variance-covariance matrix as their overarching aggregation method and so allow for dependency in stress by moving the entire correlation matrix to stress levels.
- There are high levels of diversification within the life insurance risk module, as observed in 2014. However, this is based on correlations often set near zero, which may be more of a "default assumption".
- There is generally lower diversification within the market risk module, similar to 2014, but there are large disparities between participants.



Data and Methodology

Life risks module

We asked participants about the data used for establishing dependencies within the life insurance risk module and their responses were as shown in Figure 6.1.

The wide use of expert judgement is in line with expectations and a number of participants use benchmarking or their own historical data to support this judgement.

We asked participants for a range of qualitative and quantitative information on their aggregation methodology and data as applied to the members of the Life risk module. Aggregation approaches taken for this module are presented in Figure 6.2.

The results show a Gaussian copula is the most popular aggregation method for the life insurance sub-risk module, however there are still a range of approaches being adopted.

Figure 6.1: Data sources used by survey participants in determining correlations within the life risk module

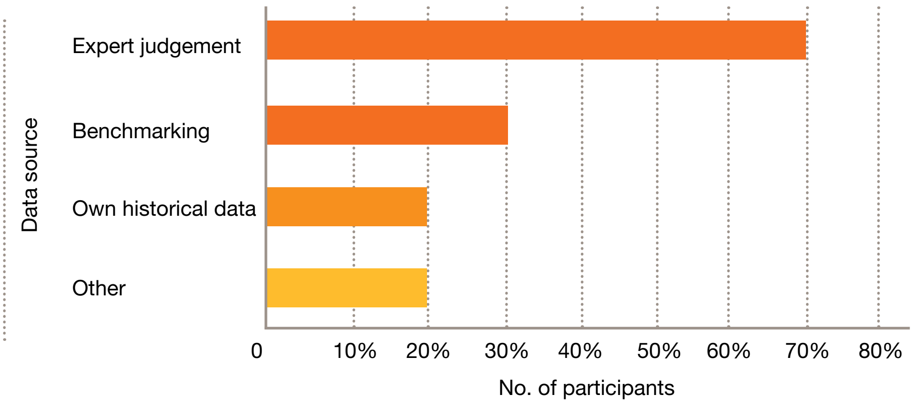
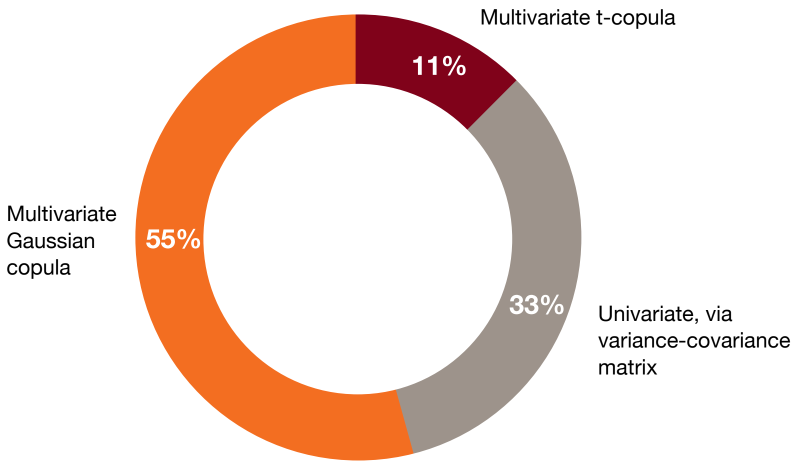


Figure 6.2: Distribution of methodology used by survey participants in the aggregation of risks within the life risks module

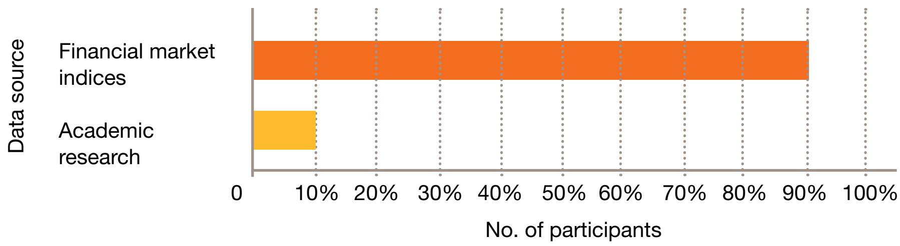


Market Risks Module

Most participants use asset market data to determine dependencies within the market risk module. Figure 6.3 illustrates the data used by participants for market risk.

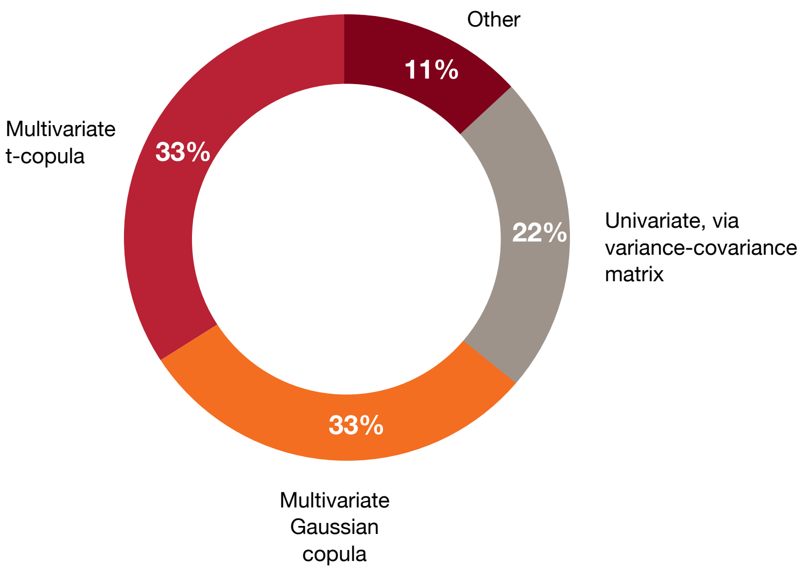
However, the data period used by participants varied widely with participants choosing periods ranging from 5 to 10 years to over 50 years. There seems little consensus in the data period most appropriate to capture these dependencies.

Figure 6.3: Data sources used by survey participants in determining correlations within the market risk module.



A variety of approaches have been taken for aggregation of the market risk module, as illustrated in Figure 6.4.

Figure 6.4: Distribution of methodology used by survey participants in the aggregation of risks within the market risks module.



Dependencies

We asked participants for the dependencies assumed between key risks.

We have applied the following definitions for the various levels of correlation:

- High: 100% - 67%
- Medium: 66% - 34%
- Low: 33% - 1%
- Nil: 0%

In this case, a positive dependency means that there is an assumed connection between losses resulting from two risk factors, for example the risk of higher lapses on unit linked policies. In this section, we provide a summary of dependencies assumed by participants.

Dependencies between longevity and other life risks

Participants assume a range of correlations, both positive and negative, between mortality and longevity risks (see Figure 6.5). Nevertheless, a significant proportion of responses point to a weaker (i.e. low positive) dependency.

Likewise, the majority of respondents assume independence of longevity and persistency level risks (see Figure 6.6). included in the comparisons of assumed dependencies within this section.

Finally, for longevity level risks and expense levels, participants have overwhelmingly chosen independence, while giving less but weighting to low positive and low negative (see Figure 6.7).

Figure 6.5: Life Risk – Longevity – Mortality

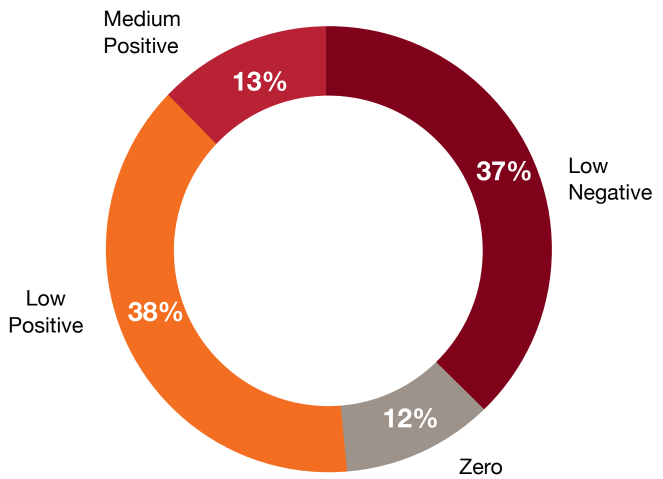


Figure 6.6: Life Risk – Persistency – Longevity

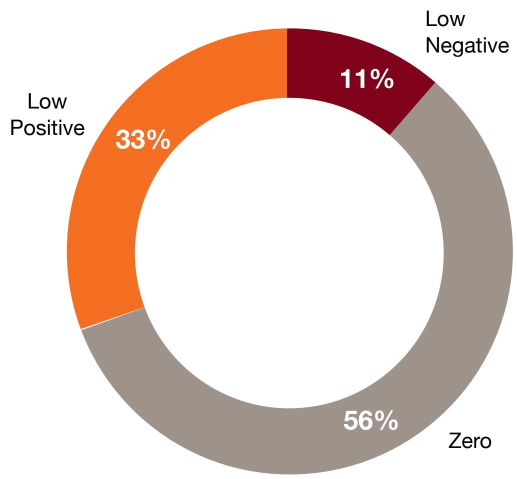
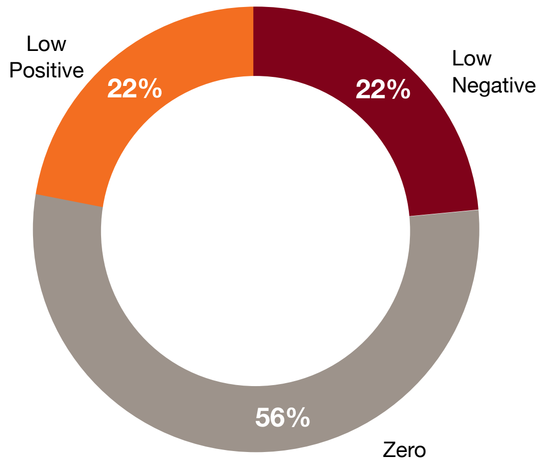


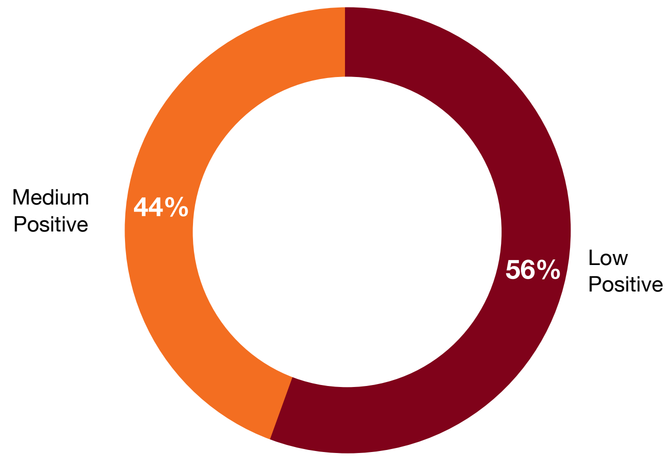
Figure 6.7: Life Risk – Expenses - Longevity



Dependencies between persistency and other life risks

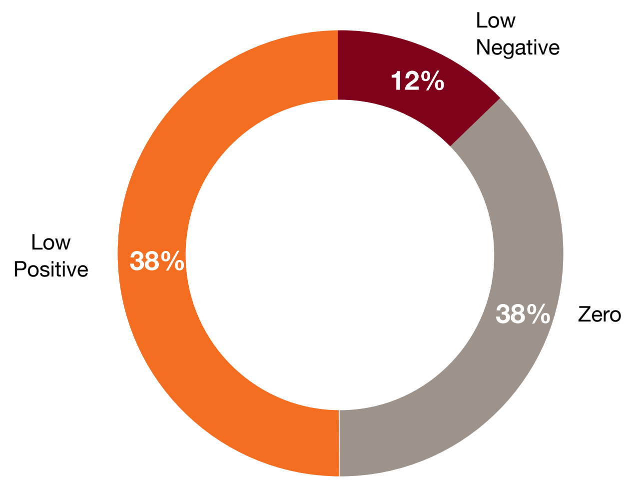
For expense levels and persistency rates (see Figure 6.8), the dependency structure is evenly split between low positive and medium positive.

Figure 6.8: Life Risk – Persistency - Expenses



For persistency and mortality risks, (see Figure 6.9), participants are evenly split between independence and a low positive correlation.

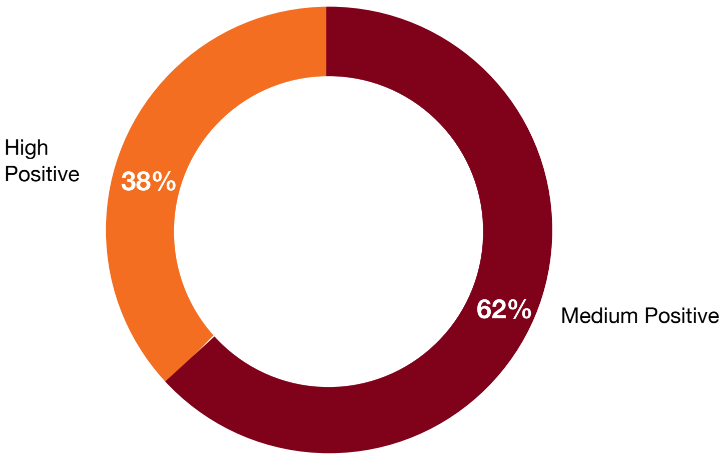
Figure 6.9: Life Risk – Persistency - Mortality



Dependencies between market risks

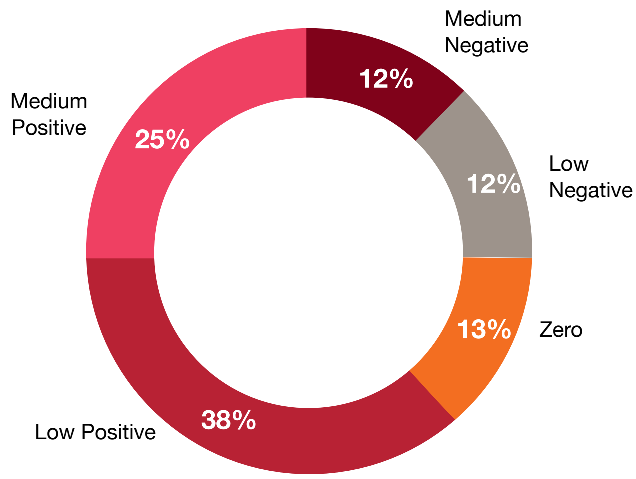
A variation in the dependency structure is observed between credit spreads and Equity risks (see figure 6.10), with half using a medium positive correlation.

Figure 6.10: Market Risk – Credit spread – Equity



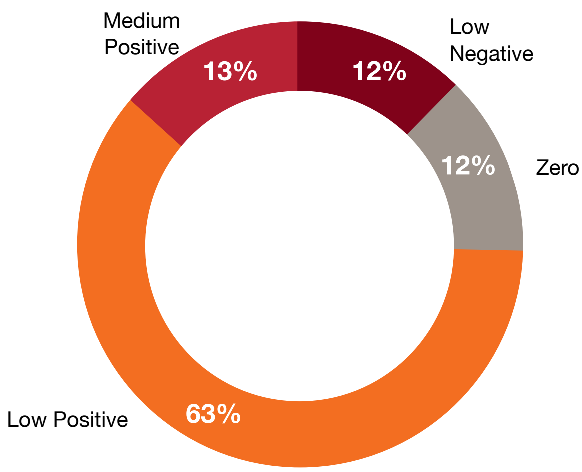
Again, a varied dependency structure is observed between credit spreads and interest rate level risks (see figure 6.11), with most using a low positive correlation.

Figure 6.11: Market Risk – Credit spread – Interest



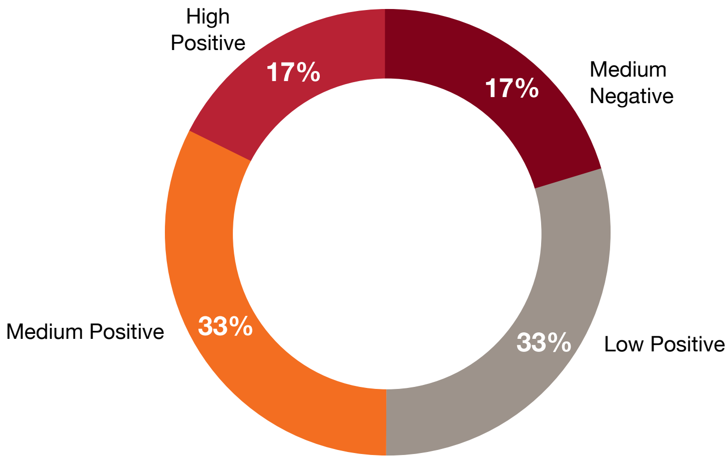
Furthermore, the market seems to have settled on a low positive dependency between equity risk and interest rate level risk (see Figure 6.12).

Figure 6.12: Market Risk – Equity – Interest



Finally, there is a divergent view as to the dependency between credit and counterparty risk (see Figure 6.13), with responses ranging from medium negative to high positive.

Figure 6.13: Market Risk – Credit - Counterparty



Diversification Benefit

We asked participants to provide a breakdown of the SCR by each of the risks separately on an Internal Model and a Standard formula basis, both pre and post diversification. From this data, we were able to determine the amount of diversification benefit realised by survey participants as part of the aggregation process.

Figure 6.14 and 6.15 show the average amount of diversification benefit for life risks and market risks respectively, expressed as a percentage of the undiversified SCR contribution. According to this metric, a score of 1 indicates that the risk is fully diversified away. The graphs highlight the risk categories that have the most potential for diversification benefit.

Figure 6.14: Average diversification benefit for each of the surveyed life risks on a stand-alone basis, expressed as percentage of undiversified risk capital.

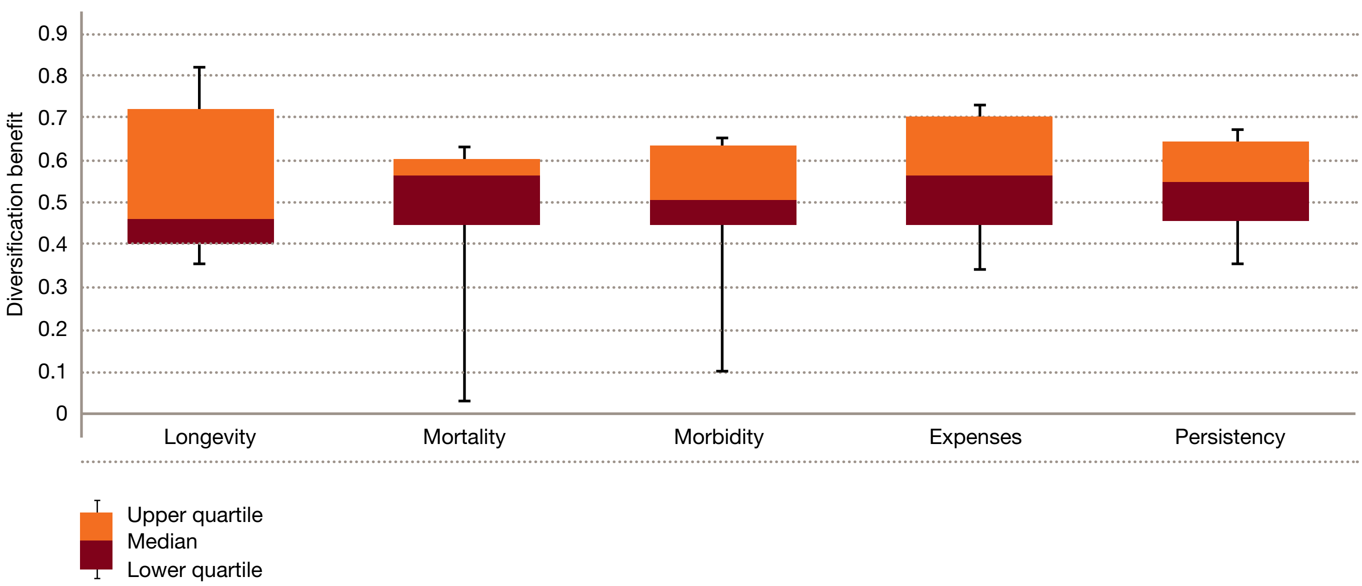


Figure 6.15: Average diversification benefit for each of the surveyed market risks on a stand-alone basis, expressed as percentage of undiversified risk capital.