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# IFRS 17: Deriving the confidence level for the Risk Adjustment: A case study for life (re)insurers

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The IFRS 17 Risk Adjustment creates challenges for (re)insurers such as how to determine the confidence level needed for disclosure purposes, and how to restate a given confidence level over different time horizons. This paper presents a solution to address these challenges and details a case study for a life company.

Under International Financial Reporting Standard (IFRS) 17 (the Standard), the Risk Adjustment is intended to measure the compensation that an entity requires for bearing the uncertainty associated with the amount and timing of the cash flows that arise from nonfinancial risk. Despite similarities with the Risk Margin under Solvency II, some key differences with the Risk Adjustment should be noted:

- The Risk Adjustment is defined from the perspective of the entity's own view of risk, whereas the Risk Margin is based on the market's view of risk.
- The calculation methodology is not prescribed. However, it must satisfy five key characteristics as defined in the Standard.[1,2]

The Standard also requires that: "An entity shall disclose the confidence level used to determine the risk adjustment for non-financial risk. If the entity uses a technique other than the confidence level technique for determining the risk adjustment for non-financial risk, it shall disclose the technique used and the confidence level corresponding to the results of that technique."[3]

This requirement is intended to help readers of financial statements compare different entities' level of risk adjustment, despite differences in methodologies.

A confidence level—Value-at-Risk (VaR)—technique can be implemented by simulating the full distribution of profits and locating the confidence level associated with the entity's Risk Adjustment. However, this requires companies to be able to derive a full stochastic distribution of cash flows based on the modelling of the underlying risk factors. This should be achievable for companies with full internal models, albeit still with operational challenges. However, for the other numerous companies, developing such a model would be a significant overhead, and therefore a pragmatic (though scientific) approach is required.

## Risk Adjustment techniques

By definition, methods other than the confidence level technique require a dedicated approach to determine the confidence level associated with a given Risk Adjustment amount. Such methods include:

- The Cost of Capital (CoC) technique, which is the approach used for the Solvency II Risk Margin. It is worth noting that, in particular, the future capital requirements as projected in the CoC formula may rely on a specific confidence level (such as the Solvency II 99.5%), but this does not correspond to the confidence level of the Risk Adjustment.
- Other methodologies that are based on adding an explicit margin on top of the biometric and behavioral assumptions, or where an adjustment to the discount rate is used to derive the Best Estimate, as well as possible techniques relying on an entity's risk aversion to derive the risk factor distribution.[4]
- In addition, a Tail Value-at-Risk (TVaR) methodology can be used; this also requires conversion because the percentile will differ from a VaR approach. However, entities using such an approach would likely already have the underlying distribution of cash flows to which the TVaR measure has been applied, which can be used to compute the equivalent confidence level to disclose using a percentile approach.

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[1] IFRS 17, paragraph B91.

[2] Milliman (December 2017). IFRS 17: Risk Adjustment. Retrieved 9 November 2020 from https://milliman-cdn.azureedge.net/-/media/milliman/importedfiles/uploadedfiles/insight/2017/ifrs-17-risk-adjustment.ashx.

[3] IFRS 17, paragraph 119.

[4] International Actuarial Association (IAA). Risk Adjustments for Insurance Contracts Under IFRS 17.

Companies that have implemented the methods described above (including the CoC approach) face the challenge of finding an appropriate technique to determine the confidence level in order to fulfill the disclosure requirement. In this context, we have proposed an operationally efficient solution using a closed-form methodology for determining the confidence level over any time horizon, based on minimal information about the portfolio structure and the risk profile.

## Deriving the confidence level

The proposed approach to derive the confidence level in an appropriate manner requires several components:

1. The Risk Adjustment amount.
2. The main characteristics of the insurance portfolio.
3. The portfolio's features, including the age, duration and sum at risk distributions.
4. The time horizon used for the confidence level calculation.
5. An appropriate modelling of risks, which satisfies the five key requirements from IFRS 17, paragraph B91.
6. An accurate calculation of the moments of the cash flow distribution, consistent with the products' and portfolios' features and the underlying modelling of risks.
7. The conversion of those statistical moments into a confidence level.

The first four components are the entity's inputs to the solution. The latter three steps are embedded in our solution to derive the Risk Adjustment, which are described in the following subsections.

### THE MODELLING OF RISKS

To illustrate the approach we focus on longevity and mortality risks and we describe a possible approach for modelling four main sources of risk; namely the level, volatility, trend and catastrophic risks. Note that such a decomposition of risks is inherited from Solvency II and is proven to be useful for satisfying the required characteristics of the Risk Adjustment.[5]

**Level risk** refers to the uncertainty in the initial mortality estimate. Typically, the experience mortality rates have been estimated using a limited number of policies (exposure) and sampling fluctuations remain in the experience mortality death rate estimate. A classic approach to level risk is to consider that the number of deaths follows a binomial distribution with parameters of the exposure-at-risk and the death rate. Given that any trend assumption applies to the initial base mortality table, the level risk is often considered to impact the uncertainty of the future cash flows throughout the projection horizon. Note that level risk can also refer to "positioning risk" in the context where a relational model is used to derive the experience mortality of the insured population as a function of the general reference population mortality.

**Volatility risk** relates to the sampling risk arising from the random outcomes of claims during each projection year. For a term assurance product, for example, it relates to the fact that, subject to the exposure, the number of deaths is random and does not follow the true underlying mortality rate (even if perfectly known), although this is the case on average. The modelling building blocks for volatility risk are similar to level risk, although the uncertainty arises in this case each year (compared to level risk, which relates to a single initial outcome—albeit impacting all future projection years).

**Trend risk** relates to the potential adverse development of the risk trend over time. For capturing trend risk, a Lee-Carter model may be appropriate; this can be written as follows:

$$\ln q(x,t) = \alpha(x) + \beta(x)\kappa(t),$$

where $\alpha(x)$ models the shape of mortality over ages, $\kappa(t)$ drives the evolution of mortality over time and $\beta(x)$ specifies the sensitivity of age $x$ to the overall mortality improvement $\kappa(t)$.

The $\kappa(t)$ time series forecasts can be based on a random walk with drift specified as follows:

$$\kappa(t+1) = \kappa(t) + \mu + \sigma\epsilon(t+1),$$

where $\mu$ is the trend, and $\sigma$ is the volatility parameter; the $\epsilon(t)$ are i.i.d. standard normal realisations (centered, unit variance).

Note that other modelling frameworks can also be considered to capture other sources of risk around the trend. For example, for the so-called "event risk" as referred to by the Prudential Regulation Authority (PRA) in the UK,[6] the drift $\mu$ itself can be considered as stochastic, allowing the company to model a change in the long-term risk view due to events such as the announcement of medical breakthroughs, new screening methods, changes in government health policy or recurrent errors in mortality data that is then updated,[7] for example. This component is more generally captured in some Solvency II internal models.

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[5] Note here that we describe such interpretations and modelling for illustrative purpose only and that the risk taxonomy and modelling may differ in different entities' views and contexts. Also, the justification of the five key requirements as per IFRS 17, paragraph B91, requires a dedicated analysis, which is beyond the scope of this present paper.

[6] PRA (15 January 2016). Reflections on the 2015 Solvency II Internal Model Approval Process. Retrieved 9 November 2020 from https://www.bankofengland.co.uk/-/media/boe/files/prudential-regulation/letter/2016/sam-woods-reflections-2015-solvency-ii-internal-model-approval-process-jan-2016.

[7] Boumezoued, A. (13 May 2020). The Cohort Effects That Never Were. Milliman White Paper. Retrieved 9 November 2020 from https://www.milliman.com/en/insight/the-cohort-effects-that-never-were.

**Catastrophic risk** corresponds to the risk arising from an external event, such as a pandemic, an epidemic or a heat wave, that creates a one-off temporary increase in the mortality assumption. The basic model for such risks is a frequency/severity approach, under which the death rate for age $x$ in year $t$ can be written as:

$$q(x,t)+\lambda(x)\Delta(t),$$

where:

- $\Delta(t)=I(t)S(t)$, with $I(t)$ a Bernoulli random variable that is 1 with some probability $p$ and 0 with probability $(1-p)$, and $S(t)$, a random severity component which captures the magnitude of the event in case of occurrence,
- $\lambda(x)$ captures the sensitivity of age class $x$ to the occurrence of the catastrophic event, i.e., how the mortality excess $\Delta(t)$ should be adjusted to reflect an age-specific mortality increase.

If one focuses on pandemic/epidemic risk, one can resort to stochastic versions of Susceptible-Infected-Recovery-Death compartmental models to obtain a refined view on the distribution of excess deaths, as currently used in some Solvency II internal models.[8]

In addition to the risks outlined above, the Risk Adjustment calculation shall include other nonfinancial risks such as lapse, morbidity or expenses. Best practice models can also be implemented for such risks, as are used for lapse risk in this paper. A relevant dependency structure then needs to be derived to be able to capture the aggregate distribution characteristics.

## MOMENTS CALCULATION

Based on a specific risk modelling framework, such as described in the previous section, the aim is to derive closed-form formulas for the calculation of the moments of the aggregate future cash flows.

Initial work has been done in this direction by some authors[9] who considered volatility risk only, and a calculation technique based on a recursive conditioning to the portfolio exposure. The generalisation of the derivation of such moments can be challenging, depending on the products and scope of risk factors at stake.

Considering annuities in payment, for example, with a number of insureds with age $x_0$ at valuation year $0$, $N(x_0,0)$, the portfolio evolves due to mortality as follows:

$$\begin{aligned} &N(x_0+t,t)\\ &=N(x_0+t-1,t-1)\big(1-q(x_0+t-1,t)\big)\\ &=N(x_0,0)\prod_{k=1}^{t}\big(1-q(x_0+k-1,k)\big), \end{aligned}$$

where $q(x,t)$ is the death rate which applies for age $x$ in year $t$.

The exposure drives the annuity amounts paid in each year $t$, which can be written as:

$$A(t)=\sum_{i=1}^{N(x_0+t,t)} A_i(x_0+t,t),$$

where $A_i(x_0+t,t)$ is the annuity amount (considered annual for illustration purposes) for insured number $i$ among all insureds with initial age $x_0$ and still alive in year $t$.

While the volatility risk component will arise from low values of the exposure $N(x_0+t,t)$, combined with the heterogeneity in the annuity payments $A_i(x_0+t,t)$ in the portfolio, the other sources of risk (level, trend and catastrophic) will provide stochastic paths for the death rate over time. In this context, due to the recursive calculation of the exposure and the complexity of the modelling of each underlying risk, the derivation of the moments is split into two steps:

- First, consider each risk separately, and compute the moments of the liability cash flows distribution subject to each risk.
- Second, perform the aggregation of those risks in a latter step to derive the moments of the aggregate distribution.

The first step to derive such a closed-form solution relies on a classic—rather useful—toolbox including in particular some Taylor expansions when required. This allows the computation of the moments up to order three for each marginal risk; noting that the third-order moment allows one to measure the asymmetry of the risk distribution.

The purpose of the second step is to aggregate the distributions in a closed-form manner to recover the aggregate statistics (variance and skewness). The aggregation problem is standard when relying only on second-order moments, but remains challenging when third-order moments are involved. Theoretical solutions do exist that allow the appropriate representation of the risk variables in the space of polynomials of Gaussian distributions, then making the computations possible under those representations.

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[8] Boumezoued, A. & Titon, E. (March 2020). Pandemic Risk Modelling in Solvency II Internal Models: Example of COVID-19.Milliman White Paper. Retrieved 9 November 2020 from https://milliman-cdn.azureedge.net/-/media/milliman/pdfs/articles/pandemic-risk-modelling.ashx.

[9] Chevallier, F., Dal Moro, E., Krvavych, Y., & Rudenko, I. (2018). Probability of sufficiency of the risk margin for life companies under IFRS 17. International Congress of Actuaries.

### PERCENTILE APPROXIMATION TECHNIQUES

One approach for then determining the Risk Adjustment percentile is based on the Cornish-Fisher expansion, which provides an approximation of the Value-at-Risk at level $\alpha$ based on the first order moments of the distribution; restricted to using moments up to skewness only, the formula is as follows:

$$VaR_\alpha(Y) \approx \mathbb{E}[Y] + \sqrt{Var(Y)}\left(z_\alpha + \frac{1}{6}(z_\alpha^2 - 1)S(Y)\right),$$

where $z_\alpha$ is the $\alpha$-percentile of the standard normal distribution and where $S(.)$ is the skewness function, defined as:

$$S(Y) = \frac{\mathbb{E}[(Y - \mathbb{E}[Y])^3]}{Var(Y)^{3/2}}.$$

Note that extensions of this formula are available involving kurtosis or even higher-order moments. Interestingly, it has been shown in practical actuarial contexts how the approximation using skewness only is rather accurate for typical percentile values as expected for an IFRS 17 Risk Adjustment calculation.[10]

## Life company case study

In this section, we illustrate the derivation of the percentile level for three types of products:

- Annuities in payment
- Term Assurance (regular and single premium)
- Savings

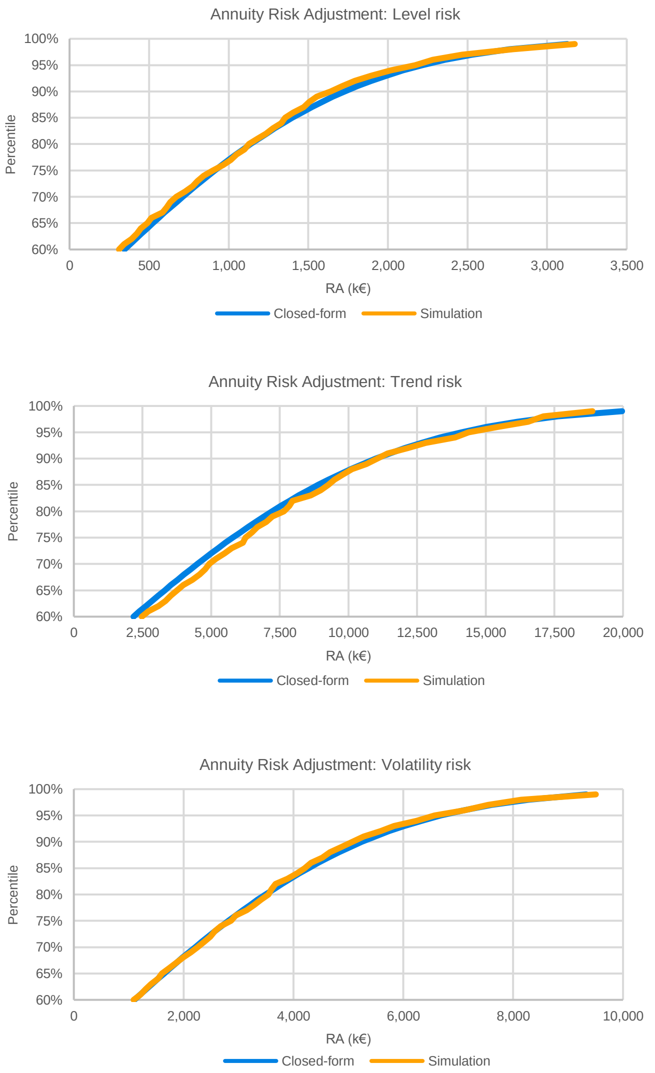
For each product, we compare the derivation of the Risk Adjustment using the closed-form methodology to a full simulation approach. This allows an assessment of the accuracy of the closed-form approach and to identify its range of validity in terms of both percentile level and type of risk.

The illustrations here rely on sample portfolios and standard sets of base assumptions in terms of mortality, lapse, yield curves and product-specific features. Risk models are also specified based on general market practice. All cash flows were projected for a period of 40 years, using a monthly time-step. For the purpose of illustration, we consider a multiyear approach with a five-year risk horizon. In the graphs which follow, the Risk Adjustment amount is displayed on the y-axis and the percentile level in the range of 60% to 99% can be read on the x-axis. The results from the full distribution approach are depicted in orange, while those from the closed-form approach are presented in blue.

### ANNUITIES

We first focus on annuities in payment and analyse the sensitivity of the confidence level derived from the closed-form approach for the three longevity risk components: level, trend and volatility, as depicted in Figure 1.

FIGURE 1: RISK ADJUSTMENT DISTRIBUTION, ANNUITIES



From this figure, we can see that the closed-form approach provides the confidence level with good accuracy. Note that no lapse risk nor mortality catastrophic (CAT) risk are included for this product.

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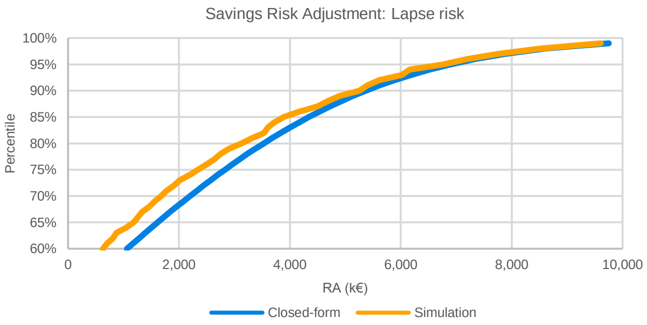
[10] Dal Moro, E., & Krvavych, Y. (2017). Probability of sufficiency of solvency ii reserve risk margins: Practical approximations. ASTIN Bulletin: The Journal of the IAA, 47(3), 737-785.

## SAVINGS

We now consider a savings product, and show the results obtained for lapse risk in Figure 2.

**FIGURE 2: RISK ADJUSTMENT DISTRIBUTION, SAVINGS**



Discrepancies appear for the lapse risk for savings, which can be up to around 5% in terms of percentile conversion for the lowest Risk Adjustment amounts. This particular case is depicted here to illustrate the sensitivity of the assumptions underlying the closed forms and the prudence required when applying such techniques when using high-volatility parameters over a multiyear horizon. The skewness term is driving most of the discrepancy, which is typical of compounded stochastic (lapse) rates over a future time horizon (here five years). Those discrepancies tend to reduce if one decreases the time horizon or the volatility parameter. Discrepancies can be avoided by including the skewness term in the closed-form calculation if necessary, as a natural extension of the present approach.

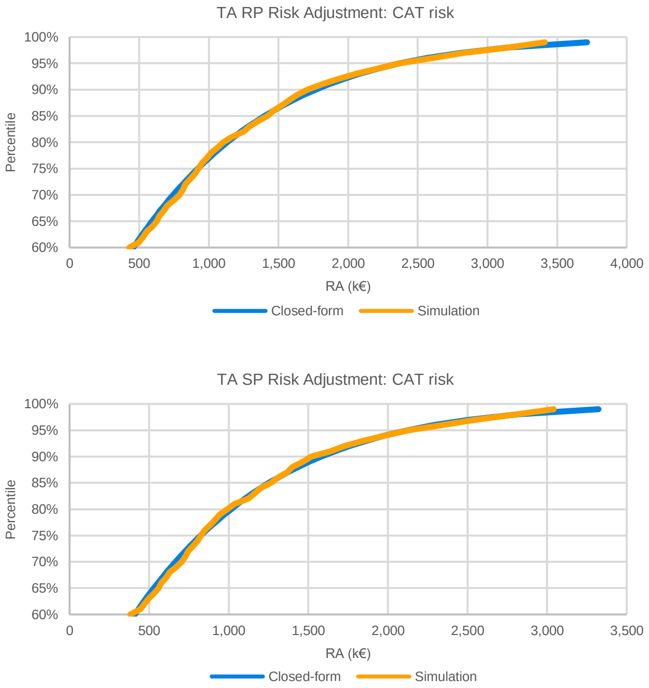
## TERM ASSURANCE

We then illustrate the derivation of the confidence level for mortality CAT risk in Figure 3, for Term Assurance with either a single premium (SP) or regular premiums (RPs).

We observe a good fit compared to the simulated results, with some differences, although minor, for the higher percentiles. This is not expected to be an issue given the typical confidence levels proposed in the market. From a modelling perspective, it is nevertheless interesting to recall why such approaches could not be used for very high percentiles, say the 99.5% Solvency II capital requirements calculation:

- The Cornish-Fisher expansion at this does not perfectly replicate the target at extremely high percentiles; in general, we find slightly lower accuracy above a 95th percentile. Again, this is a minor issue given that lower percentiles will typically be used for the Risk Adjustment.
- In addition, the skewness of the distribution has more impact at higher percentiles, and thus can be less well replicated by the closed forms.

**FIGURE 3: RISK ADJUSTMENT DISTRIBUTION, TERM ASSURANCE**



## SENSITIVITY WITH RESPECT TO RISK HORIZON

In the charts in Figure 4, a sensitivity analysis has been performed with respect to the risk horizon. The results are depicted for the annuity product and the longevity trend risk factor for a risk horizon of one, five and 10 years.

**FIGURE 4: RISK ADJUSTMENT DISTRIBUTION WITH RISK HORIZON, ANNUITIES**

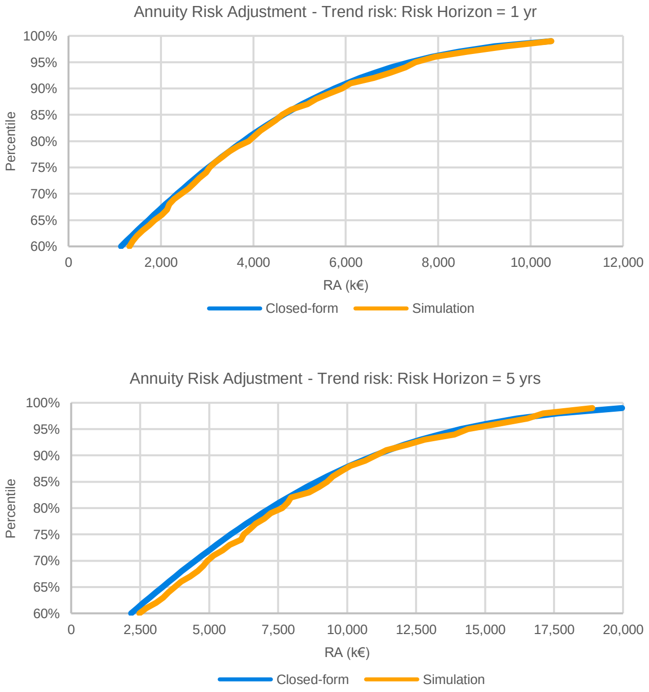
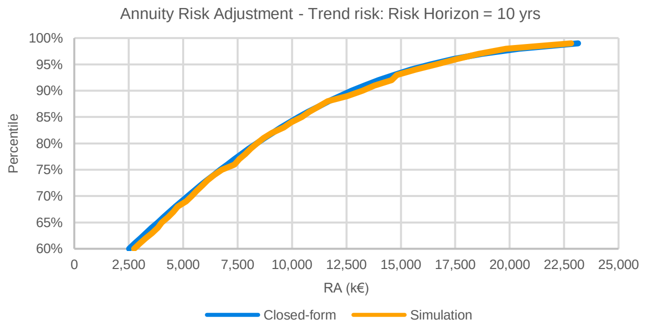


**FIGURE 4: RISK ADJUSTMENT DISTRIBUTION WITH RISK HORIZON, ANNUITIES (CONTINUED)**



Stability is observed with the three time horizons considered. It is recalled that the closed-form methodology can be applied to any time horizon, from one year up to the ultimate term.

## Summary

The Risk Adjustment under IFRS 17 poses many challenges for insurers, including how to determine the confidence level and restate a given confidence level over different time horizons. This paper shows that a closed-form solution can address these challenges for (re)insurers in an operationally efficient and accurate way.

## How can Milliman help?

Milliman has a depth of experience and expertise in IFRS 17, having closely followed its development over the past 20 years and currently supporting IFRS 17 developments for a wide range of companies.

We are therefore well placed to offer the following services:

- Training on IFRS 17 concepts, including Risk Adjustment methodologies and challenges
- Assistance with IFRS 17 gap analysis and normative analysis
- Development of IFRS 17 Risk Adjustment modelling framework and calculation processes
- Derivation of the IFRS 17 Risk Adjustment confidence level based on our dedicated solution
- Derivation of IFRS 17 discount rate structures encompassing liquidity features of insurance contracts
- Implementation of new or updated actuarial models to meet IFRS 17 requirements (e.g., IFRS 17 granularity, contract boundaries, liability for incurred claims (LIC) and liability for remaining coverage (LRC), attributable expenses)
- Defining the transition strategy including impact analysis
- Implementation of an IFRS 17 system solution through our award-winning Integrate® platform
- Use of our IFRS 17 actuarial calculation solution based on our award-winning Milliman Mind platform
- Midterm planning in an IFRS 17 context
- (Re)defining key performance indicators (KPIs) under IFRS 17

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If you have any questions or comments on this paper or any other aspect of IFRS 17, please contact the consultants below or your usual Milliman consultant.

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