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Undertaking specific parameters under solvency II: reduction of capital requirement or not?

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Abstract Solvency II regulation provides different approaches for the calculation of the solvency capital requirement (SCR): standard formula with simplification, standard formula, standard formula with undertaking specific parameters (USP), partial internal model and full internal model. In particular this regulation describes a subset of the Standard Formula market parameters (standard deviations) that may be replaced by USP, in order to calculate the SCR deriving from Premium and Reserving Risks of a Non-Life insurance company. This paper aims to explain the data requirements, methodologies and results according the so-called standardized methods proposed in the Solvency II regulation for the USP. Applying the standardized methods to three companies respectively of small, medium and large sizes and developing some sensitivity analysis, regarding the change in data from year to year, peaks and other issues which standardized methods look sensitive, the paper shows when the USP could reduce the SCR in comparison with the Standard Formula approach.

Keywords Undertaking specific parameters · Premium risk · Reserving risk · Solvency II

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1 Introduction

Solvency II provides different approaches for the calculation of the solvency capital requirement (SCR): standard formula (SF) with simplification, standard formula, standard formula with undertaking specific parameters (USP), partial internal model (PIM) and full internal model (IM).

These methods are progressively more representative of company risk profile but also less easy to implement. The SF with USP is typically the first step in order to obtain capital requirements more calibrated on the risk profile of a company than using SF, and less complex than an Internal Model.

According to article 104 of Solvency II directive (European Parliament [15]), within the design of the SF, insurance and reinsurance undertakings may replace a subset of its parameters (market-wide parameters) for each line of business (LoB) by specific parameters of the undertaking when calculating SCR for Non-Life and Health underwriting risk module. Standard deviations on 1 year time horizon for premium and reserve risks belong to this subset.

One year volatility modelling has received wide coverage in actuarial and statistical literature. Starting from the seminal work by AISAM-ACME [1], Ohlsson and Lauzeningks [21] describe simulation approaches for the one-year reserve risk and present a discussion on the one-year premium risk and its relation to the premium reserve. Diers [9] presents the idea of re-reserving applied in modelling reserve risk and premium risk. Gisler [16] explains how one year reserve and premium risks can be estimated under the Swiss Solvency Test. Appert et al. [2] exhibits a model proposing closed-form expressions for the one-year prediction error of the Claims Development Result in a multivariate framework. This model relies on a framework, which corresponds to the bivariate version of the Mack model [18].

In the technical specifications of the Quantitative Impact Studies 5 (QIS5), published on 5th June 2010, six standardized methods have been shown: three for premium risk and three for reserve risk (see CEIOPS [4, 5]). An analysis for the Italian market of QIS5 USP results has been shown in Cerchiara and Santoni [6]. Discussions on strengths and weaknesses of USP approach are given in Bulmer [3]. Cerchiara and Magatti [7] show how premium risk standard deviation can be calculated using a PIM, based on Generalised Linear or Additive Models, with a numerical comparison with CEIOPS approach on USP.

In October 2010, EIOPA (ex CEIOPS), has been committed to carry out a comprehensive revision of the calibration of the premium and reserve risk factors in the Non-Life and Health underwriting risk module of the SCR standard formula (see EIOPA [10–12]).

New calibration methods for USP have been introduced by the “Delegated Act Solvency II” (DA) published on 10th October 2014 (see EIOPA [13] and European Commission [14]). In particular, annex XVII of DA shows three new calibration methods for USP (and not six), one for premium risk and two for reserve risk.

The theoretical method underlying method 1 for premium and reserve risks is one of the four methods tested by the “Joint Working Group—JWG—on Non-Life and

Health NSLT Calibration" in the subsection Lognormal Models with Second Variance Parametrisation (see EIOPA [10]).

The loss reserving method underlying method 2 for reserve risk is the well-known Merz-Wüthrich model (Merz and Wuthrich [19, 20]).

Following De Felice and Moriconi [8], where the authors show fitting tests of standardized methods in order to get USP approval from the supervisor using data of Italian insurance market, this paper aims firstly to give a theoretical background of these new standardized methods and then to show weakness and strengths of the SF with USP by some pseudo-real case studies for the Italian market.

The paper is structured as follows. In Sects. 2 and 3 we describe the theoretical approach of the standardized methods for premium and reserve risks. In Sect. 4 we give some practical details on the implementation of these methods by the Software R. Section 5 contains our analysis by applying the standardized methods to three companies data respectively of small, medium and large sizes and developing some sensitivity analysis, regarding the change in data from year to year, peaks and other issues which standardized methods look sensitive. Finally Sect. 6 contains some concluding remarks.

2 Standard formula with undertaking specific parameters: calibration methods

SCR for Non-Life underwriting risk is derived combining capital requirements for the Non-Life sub-risks: premium and reserve, lapse and catastrophe risks.

In this paper, we deal with the two sources of underwriting risk that are joined in the SF in a submodule: premium risk and reserve risk.

Premium risk results from fluctuations in the timing, frequency and severity of insured events while reserve risk results from fluctuations in the timing and amount of claim settlements. For this submodule, capital requirement ($\mathrm{SCR}_{\mathrm{NL}}$) is obtained as follows:

$$\mathrm{SCR}_{\mathrm{nl\ prem\ res}} = 3 \cdot \sigma_{\mathrm{nl}} \cdot \mathrm{V}_{\mathrm{nl}} \tag{1}$$

where

(a) V_{nl} denotes the volume measure for Non-Life premium and reserve risks determined in accordance with Article 116 of DA;

(b) σ_{nl} denotes the standard deviation for Non-Life premium and reserve risks determined in accordance with Article 117 of DA, combining the σ_{s} according to the correlation matrix between each segment.

We focus our attention on σ_{s}:

$$\sigma_s = \frac{\sqrt{\sigma^2_{(prem,s)} \cdot \mathrm{V}^2_{(prem,s)} + \sigma_{(prem,s)} \cdot \mathrm{V}_{(prem,s)} \cdot \sigma_{(res,s)} \cdot \mathrm{V}_{(res,s)} + \sigma^2_{(res,s)} \cdot \mathrm{V}^2_{(res,s)}}}{\mathrm{V}_{(prem,s)} + \mathrm{V}_{(res,s)}} \tag{2}$$

If we assign market wide standard deviations to $\sigma_{(prem,s)}$ and $\sigma_{(res,s)}$, we are implementing Standard Formula. According to article 218 of DA, in order to obtain results more entity specific, standard deviations for premium and reserve risks may be estimated using the calibration methods published in annex XVII of the DA.

EIOPA calibrated prudently the market wide standard deviations to obtain capital requirements that give protection, with a given probability, to all types of companies: with small, medium and large dimensions. This means that pooling risk is not taken in account, i.e. the volatility of the underwriting risk does not decrease for increasing portfolio dimensions. For this reason, undertaking specific standard deviations could be more representative of specific company risk profile.

As in QIS5 methods, USP (for both risks) derives from a credibility approach, where final USP is obtained through a linear combination of market wide volatility and an estimation of specific company volatility.

In the following subsections, we describe the main features of the three standardized methods of the DA, using the framework shown in De Felice and Moriconi [8].

2.1 Method 1: premium and reserve risk

The standardized method 1 of DA is the same for premium and reserve risks, with the only differences regarding the data used for calibration. As mentioned above, the theoretical method underlying method 1 derives from the "Joint Working Group on Non-Life and Health NSLT Calibration" in the subsection Lognormal Models with Second Variance Parametrisation. However, method 1 is obtained through a reparametrization of the JWG estimation function and using data of the specific company rather than using the entire insurance market data: in the JWG methods, there is a double sum operator, one for accident years and one for insurance companies. The last one does not appear in DA methods because the aim is calibration of standard deviations for a specific company and not for the whole market.

Both for premium and reserve risks, the USP is calculated as follows:

$$\sigma_{(*,s,USP)} = c \cdot \hat{\sigma}\left(\hat{\delta}, \hat{\gamma}\right) \cdot \sqrt{\frac{T+1}{T-1}} + (1-c) \cdot \sigma_{(*,s)} \tag{3}$$

Credibility factor c varies according to the LoB considered and the number of years T (accident years in premium risk method and financial years in reserve risk method) for which data are available.

Reasonably, the bigger the length of time series the greater is the credibility given to the undertaking specific standard deviation $\hat{\sigma}$ and smaller to the market wide standard deviation $\sigma_{(prem,s)}$.

Undertaking specific standard deviation is defined as follows:

$$\hat{\sigma}\left(\hat{\delta}, \hat{\gamma}\right) = exp\left(\hat{\gamma} + \frac{\frac{1}{2}T + \sum_{t=1}^{T} \pi_t(\hat{\delta}, \hat{\gamma}) \cdot ln\left(\frac{y_t}{x_t}\right)}{\sum_{t=1}^{T} \pi_t(\hat{\delta}, \hat{\gamma})}\right) \tag{4}$$

where

$$\pi_t\left(\hat{\delta},\hat{\gamma}\right)=\frac{1}{ln\left(1+\left((1-\hat{\delta})\right)\cdot\frac{\bar{x}}{x_t}+\hat{\delta}\right)\cdot e^{2\hat{\gamma}}} \tag{5}$$

$$\bar{x}=\frac{1}{T}\sum\nolimits_{t=1}^{T}x_t \tag{6}$$

Therefore, this model, as also method 2 for reserve risk, considers a random variable $Y=\{y_t;\ t=1,\ldots,T\}$ whose variance is obtained through its theoretical relationships with an explicative variable $X=\{x_t;\ t=1,\ldots,T\}$ which acts as volume measure.

For premium risk these variables shall consist of premiums earned x_t and aggregated losses y_t, i.e. the payments made and the best estimates of the provision for claims outstanding after the first development year of the accident year of those claims. They have to be available for at least five consecutive accident years. The aggregated losses shall include the expenses incurred in servicing the insurance and reinsurance obligations and be adjusted for catastrophe claims, for amounts recoverable from reinsurance contracts which are in place to provide cover for the following twelve months (only when the premium risk method is applied to replace the standard parameters referred to in Article 196(1)(a)(ii) and (c)(ii)) and any other adjustments that may distort the behavior of the risk being analyzed.

For reserve risk y_t represents the sum of the best estimate provision at the end of the financial year for claims that were outstanding in segment s at the beginning of the financial year and the payments made during the financial year for claims that were outstanding in segment s at the beginning of the financial year. The variable x_t is instead the best estimate of the provision for claims outstanding in segment s at the beginning of the financial year. Data have to be available for at least five consecutive financial years, shall include the expenses incurred in servicing the insurance and reinsurance obligations and have to be adjusted for amounts recoverable from reinsurance contracts.

The functions involved in USP calculation depend by $\hat{\delta}$ and $\hat{\gamma}$, defined respectively mixing parameter and logarithmic variation coefficient. The values of δ and γ variables are the solutions that minimize the following function (Klugman et al. [17]):

$$l(\alpha|data)=\sum_{t=1}^{T}\pi_t(\hat{\delta},\hat{\gamma})\left(ln\left(\frac{y_t}{x_t}\right)+\frac{1}{2\cdot\pi_t(\hat{\delta},\hat{\gamma})}+\hat{\gamma}-ln\left(\hat{\sigma}(\hat{\delta},\hat{\gamma})\right)\right)^2-\sum_{t=1}^{T}ln\left(\pi_t(\hat{\delta},\hat{\gamma})\right) \tag{7}$$

For the purposes of optimization, mixing parameter is subject to the constraint of belonging to the closed interval [0,1]. Logarithmic variation coefficient has not constraints, but it is always negative being the logarithm of a real number belonging to [0,1].

2.2 Method 2: reserve risk

The loss reserving method underlying method 2 for reserve risk is the well-known Merz-Wüthrich model, shown in "Modelling The Claims Development Result For Solvency Purposes" (see Merz and Wüthrich [19, 20]). According to the method 2 of DA, volatility is calibrated as the ratio between the root of Mean Squared Error of Prediction (MSEP) of the Claims Development Result and the estimation of the Outstanding Loss Liabilities, considering one-year view. This undertaking specific standard deviation is then combined with market wide standard deviation through credibility coefficients, as method 1.

The data used for the calibration of USP for Non-Life reserve risk are the cumulative claims amounts for each accident year $\mathrm{i} = 0,\ldots,\mathrm{I}$ and development year $\mathrm{j} = 0,\ldots,\mathrm{J}$ with $\mathrm{I} \geq \mathrm{J}$. Data should be available for at least five consecutive accident years, adjusted for amounts recoverable from reinsurance contracts and include expenses.

The formula is the following:

$$\sigma_{(res,s,USP)} = \mathrm{c} \cdot \frac{\sqrt{\mathrm{MSEP}}}{\sum_{\mathrm{i}=0}^{\mathrm{I}} \left(\hat{C}_{(i,\mathrm{J})} - \mathrm{C}_{(i,I-\mathrm{i})} \right)} + (1 - \mathrm{c}) \cdot \sigma_{(res,s)} \tag{8}$$

The variables c and $\sigma_{(\mathrm{res,s})}$ are, respectively, the credibility factor and market wide standard deviation for the segment considered. We can observe that $\sum_{\mathrm{i}=0}^{\mathrm{I}} \left(\hat{\mathrm{C}}_{(\mathrm{i,J})} - \mathrm{C}_{(\mathrm{i,I-i})} \right)$ is the reserve estimation through the Chain Ladder method. For this reason, the DA method 2 is the same proposed in the QIS5 method 3 for reserve risk.

The cumulative payment estimate $\hat{\mathrm{C}}_{(\mathrm{i,j})}$ for accident year i and development year j is:

$$\hat{C}_{(i,j)} = C_{(i,I-i)} \hat{f}_{I-i} \cdots \hat{f}_{j-2} \hat{f}_{j-1} \tag{9}$$

where for all development years $\hat{f}_j$ denotes the development factor estimate:

$$\hat{f}_j = \frac{\sum_{i=0}^{I-j-1} C_{(i,j+1)}}{\sum_{i=0}^{I-j-1} C_{(i,j)}} \tag{10}$$

Finally, according the following formula:

$$S_j = \sum_{i=0}^{I-j-1} C_{(i,j)} \tag{11}$$

$$S_j' = \sum_{i=0}^{I-j} C_{(i,j)} \tag{12}$$

$$\hat{\sigma}_j^2 = \begin{cases} \frac{1}{I-j-1}\sum_{i=0}^{I-i-1} C_{(i,j)}\left(\frac{C_{(i,j+1)}}{C_{(i,j)}}-\hat{f}_j\right)^2 & j=0,\ldots,(J-2) \\ min\left(\hat{\sigma}_{J-2}^2,\hat{\sigma}_{J-3}^2,\frac{\hat{\sigma}_{J-2}^4}{\hat{\sigma}_{J-3}^2}\right) & j=(J-1) \end{cases} \quad (13)$$

$$\hat{Q}_j = \frac{\hat{\sigma}_j^2}{\hat{f}_j^2} \quad (14)$$

the MSEP is:

$$MSEP = \sum_{i=1}^{I} \hat{C}_{(i,J)}^2 \cdot \frac{\hat{Q}_{I-i}}{C_{(i,I-i)}} + \sum_{i=1}^{I}\sum_{k=1}^{I} \hat{C}_{(i,J)} \cdot \hat{C}_{(k,J)} \cdot \left(\frac{\hat{Q}_{I-i}}{S_{I-i}} + \sum_{j=I-i+1}^{J-1} \frac{C_{(I-j,j)}}{S_j'} \cdot \frac{\hat{Q}_j}{S_j}\right) \quad (15)$$

3 Assumptions underlying standardized methods

3.1 Method 1

Method 1 for premium and reserve risks is based on different assumptions:

- There is a linear relation between $E[Y]$ and X in a particular accident year:

$$E[Y] = \beta \quad \text{(M1M)}$$

- The variance of Y in a particular segment and accident year is quadratic in X:

$$Var(Y) = \beta^2\sigma^2[(1-\delta)\bar{X}X + \delta X^2] \quad \text{(M1V)}$$

  where $\bar{X} = \sum_{t=1}^{T} X_t$.
- Y follows a lognormal distribution $ln(Y) \sim Normal(\mu, \omega)$ where:

$$\omega = ln\{1 + \sigma^2[(1-\delta)\bar{X}X + \delta X^2]\} \text{ and } \mu = ln(\beta X) - \frac{\omega}{2} \quad \text{(M1D)}$$

- Maximum likelihood estimation is appropriate. (ML)

3.1.1 M1M

Assumption M1M could be tested using a linear regression analysis between $E[Y]$ and X. If we assume that Y_t are unbiased estimates of $E[Y]$, the analysis could be made using through the linear regression model:

$$Y_t = \beta_0 + \beta_1 X_t + \varepsilon_t \quad t = 1, 2, \ldots, T \tag{16}$$

where the error term ε in the linear regression model is independent of X, and is normally distributed, with zero mean and constant variance. We could establish if there is any significant relationship between X and Y using for example the F-test for regression.[1]

3.1.2 M1V

Whatever is the estimator of variance adopted, for the estimate and the validation of the model we can use, as for the hypothesis test on the average, the classic linear regression techniques.

3.1.3 M1D

According to the hypothesis M1D, we have to demonstrate that:

$$\{lnY_t;\ t = 1, 2, \ldots, T\}$$

is a sample from a normal distribution. In statistics, normality tests are used to determine if a data set is well-modeled by a normal distribution and to compute how likely a random variable underlying the data set is normally distributed. It should be noted that the low sample size available in these applications might cause that normality is accepted although it is absent.

The idea behind the goodness of fit tests is to measure the "distance" between the data and the distribution that should be tested, and compare that distance to a threshold value. If the distance (called the test statistic) is less than the threshold value (the critical value), the fit is considered good.

In order to test hypothesis M1D both algorithmic and graphical tests could be adopted. The logic of applying various goodness of fit tests is the same, but they differ by methods used to calculate the test statistic and critical values.

Following the De Felice and Moriconi [8] and EIOPA [10], we summarize main tests applied in this framework. The algorithmic tests assume the normality of the data as a null hypothesis (H0), and define an appropriate statistical test to discriminate with respect to the alternative hypothesis—non-normality (H1). In this context, a low value of the p value means that there is a low level of confidence that the data are really normal distributed.

Independently of the size of the sample used, the test of normality based on the p value, although it could provide decisive evidence in the sense of rejection of H0, it could not be decisive in the sense of acceptance of H0.

Among the algorithmic tests of normality, Kolmogorov–Smirnov test is a non-parametric test, based on the Empirical Distribution Function. Various studies have

[1] In R this test is very simple to implement: we could apply the *lm* function and then we calculate the F-statistics of the significance test with the summary function. If the *p* value is much less than 0.05, we reject the null hypothesis that $\beta_1 = 0$ and concluding that there is a significant relationship between the variables in the linear regression model of the data set used. The R function *lm* is used to fit linear models. It can be used to carry out regression, single stratum analysis of variance and analysis of covariance.

found that this test is less powerful for testing normality than the Shapiro–Wilk test or Anderson–Darling test, because in order to reject appropriately null hypothesis many observations have to be used.

However, other tests have their own disadvantages. For instance, the Shapiro–Wilk test does not work well with many ties (many identical values). It is built on the comparison of the variance estimator based on linear combination of order statistic of a normal variable and the traditional sample variance. The statistic W is the ratio of this estimator: being the null-hypothesis of this test that the population is normally distributed, it can be rejected if W is below a predetermined threshold.

Finally, Jarque–Bera test aims to establish simultaneously if the skewness and kurtosis estimated on the data are consistent with the hypothesis of normality. If the data come from a normal distribution, the JB statistic asymptotically has a Chi-squared distribution with two degrees of freedom, so the statistic can be used to test the hypothesis that the data are from a normal distribution. The null hypothesis is a joint hypothesis of the skewness being zero and the excess kurtosis being zero.

There are also graphical methods to test normality. An informal approach is to compare a histogram of the sample data to a normal probability curve. The empirical distribution of the data (the histogram) should be bell-shaped and resemble the normal distribution. This might be difficult to see if the sample is small, as for USP calculation. Another graphical tool for assessing normality is the normal probability plot, a quantile–quantile plot (QQ plot) of the standardized data against the standard normal distribution. Here the correlation between the sample data and normal quantiles measures how well the data are modeled by a normal distribution. For normal data the points plotted in the QQ plot should fall approximately on a straight line, indicating high positive correlation. These plots are easy to interpret and also have the benefit that outliers are easily identified. Likewise, a PP plot (probability–probability plot or percent–percent plot) is a probability plot for assessing how closely two data sets agree, which plots the two cumulative distribution functions against each other. See De Felice and Moriconi [8] and EIOPA [10] for more details, where the authors underline that M1M, MIV and M1D assumptions are not easily verifiable in presence of a limited set of data that is the typical issue of an individual undertaking.

3.1.4 ML

The hypothesis of maximum likelihood estimation appropriate is easily verifiable as directly derivable from convergence of the minimization procedure. The uniqueness of the minimum derived by optimization could be tested empirically studying the nature of the criterion function. For example, its regularity could be shown through a tridimensional graph. More simply, in the following paragraphs we will transform the criterion function into a two-dimensional function taking the grid of values that can be assumed by δ and γ. DA establishes itself the variation range of mixing parameter, while logarithmic variation coefficient has not constraints. However it is always negative being it the logarithm of a real number belonging to [0,1]. The graph below represents a typical volatility surface (see Fig. 1).

3.2 Method 2

Also in this case we follow the De Felice and Moriconi [8] notation. The data for method 2 implementation have to be consistent with the following assumptions about the stochastic nature of cumulative claims amounts:

- For all accident years the implied incremental claim amounts (as also cumulative claims amounts) are stochastically independent (M2I);
- For all accident years the expected value of the cumulative claims amount for a development year is proportional to the cumulative claims amount for the previous development year (M2M);
- For all accident years the variance of the cumulative claims amount for a development year is proportional to the cumulative claims amount for the previous development year (M2V).

Hypothesis M2M and M1M may be grouped together in a single hypothesis. If we denote with $B_0 := \{C_{0,0}, C_{0,1}, \ldots, C_{0,I}\}$ claims amount paid in the first development year M2M and M2V could be merged in the "time series hypothesis" (M2MV-Time Series Chain Ladder). There are two constants such that $f_j > 0$ e $\sigma_j > 0$ and $\varepsilon_{i,j}$ random variables, such that for $1 \le j \le J$ and for $1 \le i \le I$:

$$C_{i,j} = f_{j-1} C_{i,j-1} + \sigma_{j-1} \sqrt{C_{i,j-1}} \varepsilon_{i,j} \tag{17}$$

where $\varepsilon_{i,j}$ are conditionally independent given B_0 and identically distributed, with mean $E[\varepsilon_{i,j}|B_0] = 0$ and variance $Var[\varepsilon_{i,j}|B_0] = 1$.

3.2.1 M2MV

The expression (17) for each $j = 1, \ldots, J-1$ is a linear regression model referred to observations of two consecutive development years. If we define $x_i = C_{i,j-1}$, $y_i = C_{i,j}$ and $\omega_i = 1/x_i = 1/C_{i,j-1}$, the J weighted linear regressions are:

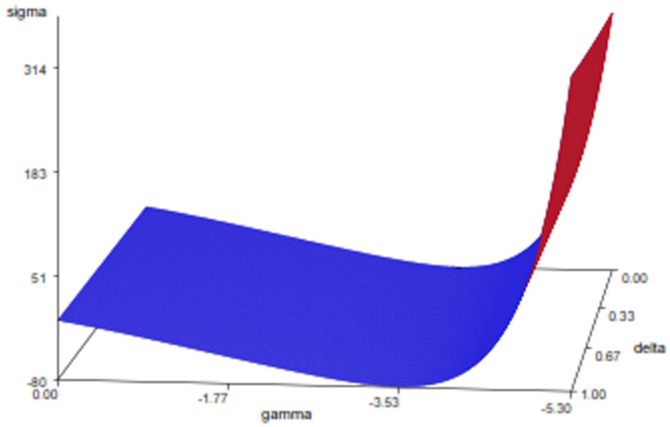

Fig. 1 The shape of a volatility surface σ(δ,γ). Source De Felice and Moriconi [8]

$$y_i = \beta x_i + \frac{\sigma}{\sqrt{\omega_i}} \varepsilon_i \quad i = 0, 1, \ldots, I \tag{18}$$

The least squares estimator of regression coefficient is:

$$\hat{\beta} = \frac{\sum_{i=1}^{n} \omega_i x_i y_i}{\sum_{i=1}^{n} \omega_i x_i^2} \tag{19}$$

This expression coincides with Chain Ladder factor estimator $\hat{f}_J$.
Moreover, the estimated variance of the error terms is:

$$\hat{\sigma}^2 = \frac{SSE}{n-1} \tag{20}$$

where:

$$SSE = \sum_{i=1}^{n} \omega_i (y_i - x_i \hat{\beta})^2 \tag{21}$$

This expression, instead, is equal to the estimator $\hat{\sigma}_j^2$ of Distribution Free Chain Ladder (Mack [18]).

The traditional hypothesis and goodness of fit tests available in the software R may be used to establish the adherence of the model to the data, thus providing a test for hypothesis M2MV. The main issue for the individual undertaking is the lack of data in order to get all the J regressions required (working with run-off triangles).

3.2.2 M2I

A method to test the independence between different accident years is to test the independence of the residuals derived from the equation *time series* (17). The idea, proposed also by Merz and Wüthrich is to verify, by means of a linear regression analysis, the absence of trend in the residuals in function of the accident years. The independence between the residuals of different accident years for a specific development year is already implicit as a result of the regression analysis performed for hypothesis M2MV. Pearson residuals test and/or empirical/simulation analysis could be an alternative. See De Felice and Moriconi [8] for more details.

4 Undertaking specific parameters calibration: algorithms in R

Method 1 for both premium and reserve risks has the same implementation algorithm having the same mathematical formulation: input data and market wide standard deviations are the only differences.

The first step is to define two vectors of input data: x_t and y_t, where each component of both vectors is referred to a specific accident year for premium risk or a specific financial year for reserve risk.

The second step is to define functions involved in USP estimation: $\hat{\sigma}$, π_t and the objective function that has to be minimized in order to obtain mixing parameter $\hat{\delta}$ and logarithmic variation coefficient $\hat{\gamma}$; both $\hat{\sigma}$ and π_t functions will be then evaluated in $(\hat{\delta}, \hat{\gamma})$.

For optimization purpose, the R function *optim* of library *stats* allows choosing different optimization methods: Nelder-Mead, BFGS, L-BFGS-B, SANN, etc. In this paper, we use method BFGS that is a quasi-Newton method also known as a variable metric algorithm and, after giving an initial value, uses function values and gradients to build up a picture of the surface to be optimized. Unlike L-BFGS-B method, the method used does not allow box constraints. However, as mentioned above for the determination of the minimum no values for the mixing parameter outside the closed interval [0,1] shall be considered.[2] For this reason, we make a change of variables using logit function:

$$y = \text{logit}(x) = \log(x/(1-x)) \quad \text{with} \quad D(y) : [-Inf, +Inf] \tag{22}$$

having:

$$x = 1/(1 + \exp(-y)) \quad \text{with} \quad D(x) : [0, 1] \tag{23}$$

Once obtained the mixing parameter and the logarithmic variation coefficient through optimization, we are able to get $\hat{\sigma}$ estimation. USP is achieved combining this estimation with market wide standard deviation for the specific risk considered, as seen in previous paragraphs.

The calibration of USP through run-off triangle type method for reserve risk (method 2) needs a different algorithm. In this case, undertaking specific standard deviation (before linear combination with market wide standard deviation) is represented by the ratio between the square root of MSEP and a value that is nothing more than the estimated reserve with Chain Ladder method.

As already seen input data shall consist of cumulative claims amounts separately for each accident year and development year of the payments, so we make in R a matrix of input data. Through this matrix, we can easily obtain both a vector with cumulative payment estimates for all accident years at the latest development year $\hat{C}_{(i,J)}$, and also the values $C_{(i,I-i)}$, with $i = 0, \ldots, I$. Therefore, we are able to estimate undertaking specific standard deviation which provides USP for reserve risk once combined linearly with market wide standard deviation of reserve risk.

5 Empirical studies

We illustrate USP results in the following application, comparing DA and QIS5 results. We consider three companies: A, B and C, with respectively small medium and large size regarding the segment Motor Vehicle Liability (MVL). For this segment the market wide standard deviations in the DA are:

[2] If we use L-BFGS-B method with box constraints rather than BFGS method, we would get almost the same results.

Table 1 Mixing parameter and logarithmic variation coefficient for each undertaking

	Undertaking A (small)	Undertaking B (medium)	Undertaking C (large)
δ	0.6360	0.0058	0.0026
γ	−2.3024	−2.7327	−3.0223

- Premium risk-gross of reinsurance: 10 % (same value in the QIS5)
- Reserve risk-net of reinsurance: 9 % (9.5 % in the QIS5).

It is worth mentioning that we analyzed pseudo data derived from the sample of the 18 Italian insurance companies which participated to joint work of ANIA and Towers Watson (see Cerchiara and Santoni [6]), with 11 accident and financial years data available for each company. According to the method 1, both for premium and reserve risk, the first step is to calculate mixing parameter and logarithmic variation coefficient through optimization. After that we are able to calculate the standard deviations and combine them with market wide standard deviations through the credibility approach in order to get USP.

5.1 Method 1: premium risk

5.1.1 Mixing parameter and logarithmic variation coefficient

In the following table we show the values of variables δ and γ that minimize objective function (7) for each company (see Table 1).

Logarithmic variation coefficient γ always assumes negative values, being the natural logarithm of a value belonging to the interval [0,1] and it depends on the company size.

We can also observe that the values assumed by mixing parameter δ for company B and C are very close to 0 (the inferior extreme of its domain).[3]

If we use Nelder-Mead method or L-BFGS-B method rather than using BFGS method for optimization, we get the same results. In particular, L-BFGS-B method allows box constraints for parameters that have to be minimized and this make unnecessary logit transformation: thereby the values of mixing parameters that with Nelder-Mead or BFGS method are approximately equal to 0 and 1, with L-BFGS-B method are exactly equal to 0 and 1.

If the objective function depend on only one variable, this trend to be addressed to the upper (or lower) edge of its domain could be justified arguing the decreasing (or increasing) nature of the same function. Depending it on δ and γ and not being R^2 an ordered set, we can not argue it. However, making some changes without change the nature of the function we can proceed with a graphical analysis.

In particular, we fix a grid of equidistant values between 0 and 1 assumed by mixing parameter: in this way objective function depends only by γ, in function of which we will minimize. The graphs obtained are the following (see Fig. 2).

[3] For many others companies analyzed in Cerchiara and Santoni [6] (not shown in this paper) mixing parameter assumes values very close to 1, the superior extreme of the domain.

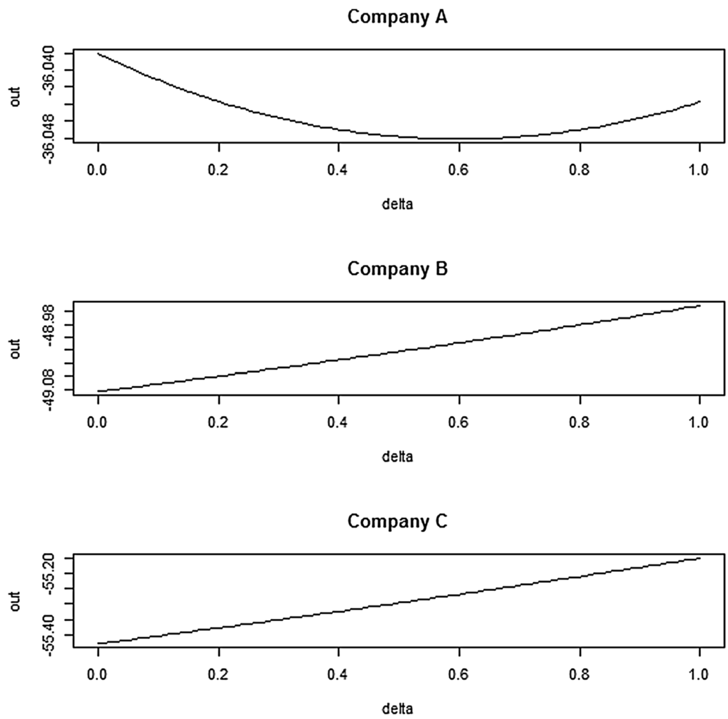

Fig. 2 Objective function trend

A sensitivity analysis performed on functions involved in USP calculation shows as, being equal logarithmic variation coefficient, the value assumed by mixing parameter does not affect (or better affects with an order never less than 10^4) the value assumed by the same functions and so neither USP. To prove it, we consider company A data, for which mixing parameter and logarithmic variation coefficient are the following:

- $\delta = 0.6360$
- $\gamma = -2.3024$

The Table 2 contains the values of function (5) evaluated with these values:

So by the formulas (3) and (4), we have $\hat{\sigma} = 0.\ 6862$ and USP = 8.2 %.

Now let **a** be a vector of ten equally spaced points in the interval [0,1] within which mixing parameter varies. The values of function (5) evalued in each element of the vector are the rows of the following matrix (see Table 3).

Having considered a vector of mixing parameters and not a single value, we obtain as many standard deviations as vector **a** components (see Table 4).

So, the values $\hat{\sigma}(\boldsymbol{a}; -2.302449)$ with $a = 0, 0.1, \ldots, 1$ differ from them and $\hat{\sigma}(0.068624, -2.302449)$ of not more than 0.003 % (difference between the biggest and the smallest components).

Table 2 The values of function π_t for each year with $\delta = 0.6360$ and $\gamma = -2.3024$

	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 8	t = 9	t = 10
π_t	111.07	104.68	100.62	97.76	96.22	97.58	99.17	97.66	94.71	101.25

Table 3 The values of function (5) evalued in each element of vector a

	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 8	t = 9	t = 10
a = 0.0	136.21	112.95	100.87	93.37	89.60	92.92	96.97	93.12	86.09	102.63
a = 0.1	131.53	111.57	100.83	94.03	90.58	93.62	97.31	93.81	87.34	102.40
a = 0.2	127.16	110.21	100.79	94.71	91.58	94.34	97.65	94.50	88.63	102.19
a = 0.3	123.07	108.89	100.75	95.39	92.60	95.06	98.00	95.21	89.95	101.97
a = 0.4	119.23	107.60	100.71	96.08	93.65	95.80	98.34	95.93	91.32	101.75
a = 0.5	115.63	106.35	100.67	96.79	94.72	96.55	98.69	96.66	92.72	101.54
a = 0.6	112.24	105.12	100.63	97.50	95.89	97.31	99.04	97.40	94.18	101.32
a = 0.7	109.06	103.91	100.59	98.23	96.94	98.08	99.40	98.15	95.67	101.11
a = 0.8	106.03	102.74	100.55	98.97	98.09	98.86	99.75	98.91	97.22	100.90
a = 0.9	103.18	101.59	100.51	99.71	99.27	99.66	100.11	99.68	98.82	100.68
a = 1.0	100.47	100.47	100.47	100.47	100.47	100.47	100.47	100.47	100.47	100.47

This is also argued by graphical analysis that shows an almost constant trend of standard deviation by varying mixing parameters (see Fig. 3).

It should be useful to remember the USP calculation formula for premium risk (3):

$$\sigma_{(prem,s,USP)} = c \cdot \hat{\sigma}(\hat{\delta}, \hat{\gamma}) \cdot \sqrt{\frac{T+1}{T-1}} + (1-c) \cdot \sigma_{(prem,s)}$$

In this formula, the only function influenced by mixing parameter is $\hat{\sigma}(\hat{\delta}, \hat{\gamma})$, while other variables are fixed or established by DA. This means that $\hat{\sigma}(\hat{\delta}, \hat{\gamma})$ behavior is totally reflected on USP behavior (see Table 5).

In fact, also in this case the differences among the components of USPs vector (one for each component of mixing parameter vector) are neglectable because always less than 0.003 %. This is argued also by graphical analysis (see Fig. 4).

Concluding, the sensitivity analysis performed shows as, fixed logarithmic variation coefficient and mixing parameter variation range imposed by DA, the value assumed by USP is not influenced by that of mixing parameter.

5.1.2 Results

In the following table are summarized USP for premium risk, after application of credibility factors combining undertaking standard deviation and market wide

Table 4 The values of function (4) evalued in each element of vector a

a	σ
0.0	0.06866
0.1	0.06865
0.2	0.06864
0.3	0.06864
0.4	0.06863
0.5	0.06863
0.6	0.06862
0.7	0.06862
0.8	0.06862
0.9	0.06862
1.0	0.06862

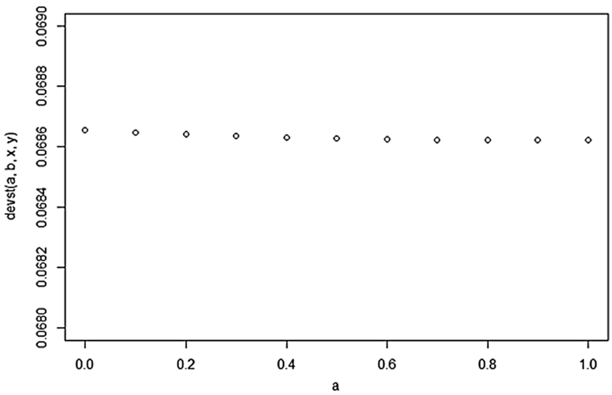

Fig. 3 Standard deviations in function of mixing parameters

Table 5 The values of USPs for each element of vector a

a	USP
0.0	0.08217
0.1	0.08216
0.2	0.08216
0.3	0.08215
0.4	0.08215
0.5	0.08214
0.6	0.08214
0.7	0.08214
0.8	0.08214
0.9	0.08214
1.0	0.08214

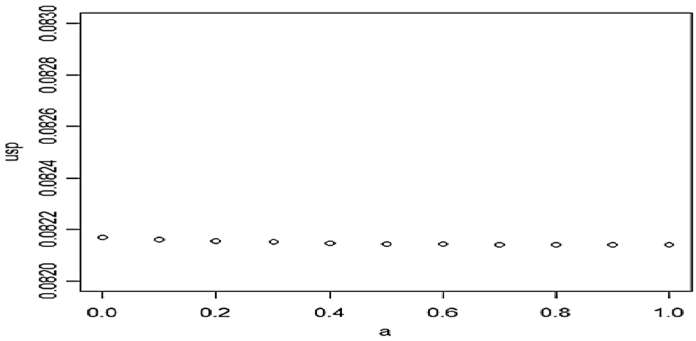

Fig. 4 The values of USPs for each element of vector a

Table 6 USP for premium risk, after application of credibility factors

	Undertaking A (small) (%)	Undertaking B (medium) (%)	Undertaking C (large) (%)
USP	8.2	6.5	5.5
	7.7, 7.4, 11.0	6.1, 4.1, 6.6	5.3, 5.1, 6.7

parameter (10 % in both QIS5 and DA). Each row is split in two sub-rows: in the upper there are the results of DA calibration methods, in the lower QIS5 calibration methods results (see Table 6).

We can see that the QIS5 result of the third method (frequency-severity approach, see Gisler [16] and CEIOPS [4]) for the undertaking A is the only one over the market wide standard deviations. Reasonably, USP are decreasing with increasing undertaking size, with a difference of 2.7 % between the biggest and the smallest.

The general consideration regarding these results is that whatever is the company size, they always are lower than DA market wide standard deviations which is 10 % for the Lob MVL. So USP approach produces a smaller SCR than SF approach for each company.

5.2 Method 1: reserve risk

5.2.1 Mixing parameter and logarithmic variation coefficient

As made for premium risk but using reserve risk data, through optimization we attain the following results for mixing parameter δ and logarithmic variation coefficient γ.

For reserve risk we have the same considerations made for mixing parameter and logarithmic variation coefficient for premium risk. In fact, also in this case the values assumed by mixing parameter are very close to the lower extreme of its definition domain, depending it on objective function behavior. To prove it

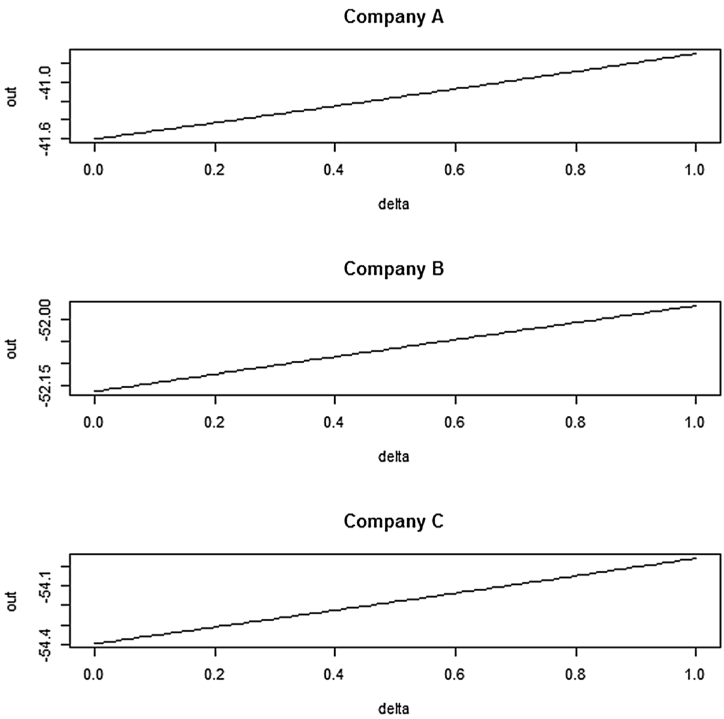

Fig. 5 Objective function trend

Table 7 Mixing parameter and logarithmic variation coefficient for each undertaking

	Undertaking A (small)	Undertaking B (medium)	Undertaking C (large)
δ	0.0008	0.0006	0.0049
γ	−2.8134	−3.1079	−3.2230

graphically, as done for premium risk, we fix a grid of equidistant values between 0 and 1 assumed by mixing parameter so that objective function depends only by γ. In this way, being it a one-variable function, we can analyze its increasing or decreasing nature. The graphs obtained are the following (see Fig. 5).

Each graph shows the reliability of results shown in Table 7 for each undertaking considered. Also for reserve risk the sensitivity analysis shows that, being equal logarithmic variation coefficient, the value assumed by mixing parameter affects the USP obtained with an order not less than 10^4.

To prove it, we consider undertaking A data. As we can see in Table 7, mixing parameter and logarithmic variation coefficient obtained through optimization are the following:

- $\delta = 0.0008$
- $\gamma = -2.8134$

Table 8 The values of function π_t for each year with $\delta = 0.0008$ and $\gamma = -2.8134$

	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 8	t = 9
π_t	311.64	280.05	267.49	252.77	239.6	288.81	304.16	296.83	263.22

Table 9 The values of function (5) evalued in each element of vector a

	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 8	t = 9	t = 10
a = 0.0	311.67	280.05	267.48	252.75	239.57	288.82	304.19	296.85	263.21	311.67
a = 0.1	307.97	279.87	268.53	255.09	242.95	287.73	301.38	294.88	264.64	307.98
a = 0.2	304.37	279.70	269.58	257.47	246.43	286.65	298.63	292.94	266.09	304.37
a = 0.3	300.84	279.52	270.64	259.90	250.00	285.58	295.93	291.03	267.56	300.84
a = 0.4	297.40	279.34	271.70	262.38	253.69	284.52	293.27	289.14	269.04	297.40
a = 0.5	294.03	279.17	272.78	264.90	257.48	283.46	290.66	287.27	270.54	294.03
a = 0.6	290.74	279.00	273.86	267.48	261.39	282.41	288.10	285.43	272.05	290.74
a = 0.7	287.53	278.81	274.96	270.10	265.42	281.37	285.58	283.61	273.59	287.53
a = 0.8	284.38	278.64	276.06	272.77	269.57	280.33	283.11	281.81	275.14	284.38
a = 0.9	281.30	278.46	277.167	275.50	273.86	279.31	280.68	280.04	276.70	281.30
a = 1.0	278.29	278.29	278.29	278.29	278.29	278.29	278.29	278.29	278.29	278.29

Table 10 The values of function (4) evalued in each element of vector a

a	σ
0.0	0.06995
0.1	0.06997
0.2	0.06999
0.3	0.07
0.4	0.07002
0.5	0.07004
0.6	0.07006
0.7	0.07008
0.8	0.0701
0.9	0.07012
1.0	0.07014

The Table 8 contains the values of function (5) evaluated with these values:

So by the formulas (3) and (4), we have $\hat{\sigma} = 0.6995$ and USP $= 8.2$ %.

Now let **a** be a vector of ten equally spaced points in the interval [0,1] within which mixing parameter varies. The values of function (5) evalued in each element of the vector are the rows of the folliwing matrix (see Table 9).

For each component of vector **a** we have an undertaking specific standard deviation (before combination with market wide standard deviation) (see Table 10).

So, the values $\hat{\sigma}(\boldsymbol{a}; -2.81343)$ with $a = 0, 0.1, \ldots, 1$ differ among them and $\hat{\sigma}(0.00085, \ -2.81343)$ of not more than 0.19 % (difference between the biggest

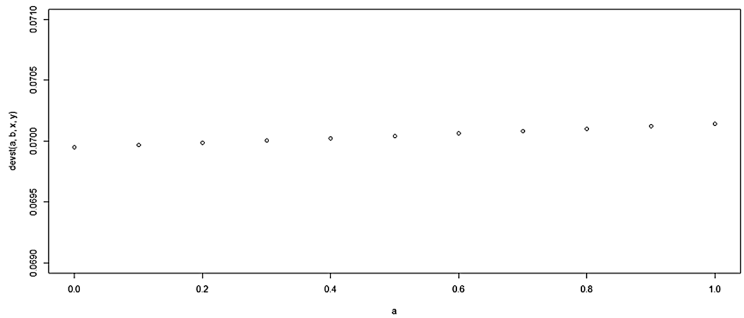

Fig. 6 Standard deviations in function of mixing parameter

Table 11 The values of USPs for each element of vector a

a	USP
0.0	0.0821
0.1	0.08211
0.2	0.08213
0.3	0.08214
0.4	0.08215
0.5	0.08217
0.6	0.08218
0.7	0.0822
0.8	0.08221
0.9	0.08223
1.0	0.08224

and the smallest components). Also a graphical analysis (Fig. 6) shows as $\hat{\sigma}(\boldsymbol{a}, -2.81343)$ takes almost the same values for each value of vector **a**.

The calculation formula of USP for reserve risk is:

$$\sigma_{(res,s,USP)} = c \cdot \hat{\sigma}(\hat{\delta}, \hat{\gamma}) \cdot \sqrt{\frac{T+1}{T-1}} + (1-c) \cdot \sigma_{(res,s)}$$

For the same reasons of premium risk, the standard deviation behavior is totally reflected on USPs that assume almost the same values for each component of vector **a** (Table 11; Fig. 7).

Concluding, the sensitivity analysis performed shows as also for reserve risk, fixed logarithmic variation coefficient and mixing parameter variation range imposed by DA, the value assumed by USP is not influenced by that of mixing parameter.

5.2.2 Results

In the following table are summarized USP for reserve risk (we call them USP_1 to distinguish them from method 2 for reserve risk results), after application of

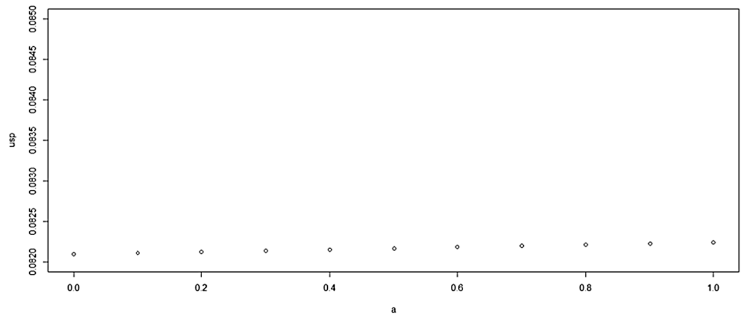

Fig. 7 The values of USP for each element of vector a

Table 12 USP for reserve risk (method 1), after application of credibility factors

	Undertaking A (small) (%)	Undertaking B (medium) (%)	Undertaking C (large) (%)
USP	$USP_1 = 8.2$ 17.2, 11.8, 7.5	$USP_1 = 6.0$ 5.7, 6.6, 6.6	$USP_1 = 5.5$ 7.5, 6.0, 4.8

credibility factors combining entity standard deviation and market wide parameter (9.5 % in the QIS5 and 9 % in the DA) (see Table 12).

About USP behavior we notice that, reasonably, USPs are decreasing with increasing undertaking size, with a difference of 2.7 % between the biggest and the smallest. USPs are always lower than DA market wide standard deviations (this is not always true for company A under QIS5), producing a reduction in SCR adopting USP approach.

5.3 Method 2: reserve risk

Implementing method 2 for reserve risk, we obtain the results reported in Table 13. In the same table, as done for method 1 (both for premium and reserve risks), there are DA and QIS5 results. We use USP_2, in order to distinguish from USP_1 derived from method 1 for the same risk.

Finally, in Table 14 we resume the USPs of both methods for reserve risk considering the DA framework.

Table 13 USP for reserve risk (method 2), after application of credibility factors

	Undertaking A (small) (%)	Undertaking B (medium) (%)	Undertaking C (large) (%)
USP	$USP_2 = 7.3$ 17.2, 11.8, 7.5	$USP_2 = 6.5$ 5.7, 6.6, 6.6	$USP_2 = 4.6$ 7.5, 6.0, 4.8

Table 14 USP for reserve risk

	Undertaking A (small) (%)	Undertaking B (medium) (%)	Undertaking C (large) (%)
USP	$USP_1 = 8.2$ $USP_2 = 7.3$	$USP_1 = 6.0$ $USP_2 = 6.5$	$USP_1 = 5.5$ $USP_2 = 4.6$

This comparison shows that the two methods (for the same risk) give similar results. However, whatever is method chosen, USP obtained are lower than market wide standard deviation (9 %), producing a reduction in SCR.

5.4 Sensitivity analysis

The tables below show the results of different sensitivity analysis conducted to demonstrate how these methods are closely linked to the individual data used but sometimes fail to catch the business trends of the company. The analysis have been conducted using medium size company (B) data, but same comments could be made for undertakings A and C (see Table 15).

For premium risk method, assuming a growing business with a positive technical trend (which results in a decrease of losses or an increase of earned premiums) volatility is not reduced, but rather increased.

Moreover, just one peak in the time series considered, whether premium or aggregate losses, results in a significant increase of estimated volatility. This is still true if total premiums vary significantly between different accident years.

The length of the time series used is a key factor in the estimation of USP: it is a multiplicative factor in USP formula (see formula (3) and (8)) which is significantly reduced if the number of years (T) used grows. Besides, as seen before, the bigger the length of time series the greater is the credibility given to undertaking specific standard deviation than market wide standard deviation. In particular, the sensitivity analysis which adds 5 years (T + 5) to the original time series gives full credibility to undertaking specific standard deviation and null credibility to market wide standard deviation, being its length 16 years.

Table 15 Sensitivity analysis—premium risk method

Premium risk	USP (%)
Original data	6.5
Peak on aggregated losses	10.6
Peak on earned premium	7.6
Decreasing losses	15.1
Increasing losses	5.1
Increasing earned premium	6.7
Decreasing earned premium	14.6
Decreasing losses and increasing earned premium	15.2
T + 1	6.0
T + 5	4.6

Table 16 Sensitivity analysis—reserve risk method 1

Reserve risk	USP (%)
Original data	6.0
Peak on claims development	9.0
Peak on opening reserve	9.6
Increasing opening reserve	8.0
Decreasing opening reserve	9.4
Decreasing claims development result	10.4
Increasing claims development result	7.1
T + 1	5.5
T + 5	3.9

Table 17 Sensitivity analysis—reserve risk method 2

Reserve risk	USP (%)
Original data	6.5
Peak of a cumulative claims amount	18.6

Loss ratio analysis shows that in some cases it does not affect the USP values, i.e. considering a shock (+10 % in each accident year) USP value does not change.

Method 1 tends to produce a higher USP factor when the experienced claims ratios have varied relatively substantially over the period over which the USPs have been calculated. For example, if the shock has an impact only on the last year, in which loss ratio moves from 79 to 97 %, USP increase of about 2 %.

The same sensitivity analysis applied to method 1 for reserve risk leads us to similar considerations (see Table 16).

About method 2 for reserve risk, simulating a significant increase in the cumulative claims amount for a specific claim and in a particular development year (e.g. due to a court decision for several deaths from the same claim), we have a significant increase in the USP, due to the high increase in the MSEP (see Table 17).

6 Conclusion

The use of USP has to be submitted to an approval process to the supervisor that needs evidence of data quality, that the USP better reflects the company's risk profile and that the assumptions of methods are met. These tests are not always easy to implement for a single undertaking, as shown before, especially with lack of data. Using USP the final result is not always guaranteed a capital gain for the company, due to the fact that USP obtained both for premium and reserve risks are closely linked to data distribution and the final results depend by the length of the time series. In particular, for all methods just one peak in time series could lead to biased standard deviation. So from year to year USP results can change dramatically, not more producing SCR reduction.

Table 18 Comparison of stressed scenarios

	Premium Risk	Reserve Risk 1	Reserve Risk 2
Peaks on losses	High impact	High impact	High impact
Peaks on premium/opening reserve	High impact	High impact	
Growing Business	High impact	High impact	
Decreasing Business	Low impact	High impact	
T+1	Low impact	Low impact	
T+5	Low impact	Low impact	

Below we summarize the main findings from the case studies in the table and further comments (see Table 18).

Premium risk method 1 tends to produce a higher USP factor when one or more of the following factors apply:

- Total premiums vary significantly between different policy years.
- The experienced claims ratios are relatively high.
- The experienced claims ratios have varied relatively substantially over the time series period from which the USPs have been calculated.
- The company has had the practice of allocating relatively prudent claims reserves for a underwriting year at the end of the first development year.
- Especially for small company, a single policy year of adverse claims experience can have a material effect on the value of the calculated USP.

Reserve risk method 1 essentially involves reviewing the run-off of the claims provisions, based only on the company's own view of its claims provisions. In summary, the company's claims provision for a policy year at the start of a financial year is compared with the sum of the company's own claims provision at the end of the financial year plus claims paid during the financial year. Reserve risk method 1 tends to produce a higher USP factor when the actual run-off of claims is different from that initially expected. Besides as shown in Bulmer [3] and Cerchiara and Santoni [6], it should be noted that a favourable reserve run-off produces the same reserve risk factor as an unfavourable reserve run-off.

Reserve risk method 2 is a method based on the MSEP of the Claims Development Result over a 1 year time horizon. The calculated mean squared error is divided by the company's own claims provision to calculate the reserve risk factor.

Another interesting outcome from the case studies is that once determined logarithmic variation coefficient and mixing parameter variation range (set by DA), the USP value is not influenced by mixing parameter δ. In "Calibration of the Premium and Reserve Risk Factors in the Standard Formula of Solvency II" we can read: "It is good to remember that with $\delta = 0$ the probability distribution of y will become bell-shaped approaching a normal distribution under the forces of the central limiting law. When $\delta > 0$ a mixing operation enters the scene that at best results in a mixed normal distribution, which in general will have more heavy tails, such as these of the Student distribution." So, δ reflects the shape of the distribution, but it doesn't seem relevant for USP values considering our numerical results. This issues will be investigated in further research on other data set.

Finally it is worth mentioning that the use of USP could be very useful also regarding the Own Risk Solvency Assessment (ORSA, see European Parliament [15]) when the undertaking have to identify whether the company risk profile deviates from the assumptions underlying Standard Formula. A better understanding and management of the specific risk profiles could lead to a lower but nevertheless eligible capital requirement. To this end, a strategic choice could be the adoption of Standard Formula with USP, but taking into account a priori the possible effects on the results from the change in underwriting, premium rates, merger and acquisition, because cherry picking is not admitted (switch from SF with USP to SF have to be approved by the supervisor, e.g. when SF with USP do not more reduce the SCR).

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