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Solvency Measures for Insurance Companies:

Is There a Room for Improvement?

DRAFT

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Abstract

Over the last few years, there has been a considerable debate in the industry and in the academic community about the accuracy and reliability of risk-based solvency measures in approximating the level of risk retained by insurance and reinsurance entities. This topic was further reinvigorated by the recent enactment of Solvency II requirements by the European Parliament[1], which should replace the current Solvency I regulations in 2012. Despite divergence of opinions about the adequacy of specific risk based measures of required solvency capital, there seems to be a general consensus that in principle, well-designed risk based capital (RBC) or solvency requirements can help achieve an efficient reduction in the expected costs of insolvencies by helping regulators to identify weak insurers and intervene well before capital falls below specified levels.[2]

The main objective of this paper is to revisit both issues – the accuracy and reliability of most common risk-based measures of insurers' solvency and the practicability of risk-based measures of solvency for corrective regulatory action. The paper also touches upon the role of financial incentives in developing the RBC estimates.

Introduction

In this paper, we investigate the practical value of the RBC approaches for insurance regulators and equity investors by applying two most well-known measures of risk based solvency (Solvency II and Swiss Solvency Test) to a portfolio of catastrophe risk for a mono-line catastrophe risk insurer. We begin by providing a brief overview of the existing literature on the main limitations of most common risk-based solvency measures. Using 15 different scenarios, we demonstrate how the RBC measures obtained for a chosen risk portfolio can be significantly reduced by exploiting common data and modeling uncertainties, which in some cases can be used to manipulate the RBC values. We then discuss how the existing system of incentives in the industry may affect insurers' decisions with regard to determination of the level of RBC. The paper concludes by offering several concrete recommendations on how to make the RBC approaches to insurers' solvency less prone to adverse incentives and potential data manipulation.

In general, insurance solvency risk can be defined as a future random value of an insurer's financial net worth, e.g. the difference between the company's equity capital and the overall

[1] The text of final Solvency II Directive was adopted by the European Parliament on April 22, 2009.
[2] Cummings et al (1995)

value of insurance claims arising from the existing insurance risk portfolio at any future point in time[3]. Solvency r*isk measures* enable to assess and quantify the risk[4]. In the simplest and most common case, a risk measure reduces the complex characteristics of underlying risk exposure to a simple number, thus enabling to quantify it.

Over the last decade, risk based measures of solvency have gained world-wide recognition through the implementation of the Basel II Agreement in banking. However, risk-based measures of solvency have been much less common in insurance,[5] where until recently the very notion of risk-based supervision has been mainly academic, except for a few countries. The situation however changed for the better with the recent passage of the Solvency II regulatory framework by the EU Parliament, which sets a concrete implementation frame-work for the implementation of RBC solvency requirements all EU countries. In addition to Solvency II, there is a variety of other standard and special risk measures[6]. In this paper we will concentrate on *Value at Risk* (VaR) and *Expected Shortfall* (ES) solvency risk measures as being most common due to their implementation requirement under the Solvency II and the Swiss Solvency Test frameworks.

The VaR is one of the most popular risk measures, mainly due to its simplicity, wide applicability and universality[7]. It is the most widely used risk measure in financial institutions for market risk and credit risk. It is used in Basel II as well as in life insurance; it is also proposed as a risk measure under the Solvency II framework. However, the Value at Risk has some serious limitations. Most criticisms zoom in on the fact that as a risk measure the Value at Risk is not sub-additive in general.[8] Sub-additivity is the mathematical equivalent of the diversification effect. In a nutshell, it means that the measure of the sum of two risks should not exceed the sum of measures of two risks. Hence, the concept of sub-additivity implies that risk can be reduced through diversification, a concept widely used in economic theory. For a sub-additive risk measure, portfolio diversification always leads to risk reduction, while for a non-sub-additive risk measure it is not the case in general. If a non-sub-additive risk measure is used, it may happen that the diversified portfolio requires more solvency capital than the original one, which is counter-intuitive and highly undesirable from the regulatory point of view[9]. Furthermore, the VaR measure does not consider the risks at the tail of distributions, which in

[3] For simplification reasons, this definition of solvency risk disregards potential claims on the company's solvency capital that may arise out of poor operational performance (e.g. fraud, failure of systems, court awards against the company, etc.), and loss in the value of company's assets.
[4] See ARTZNER et al. (1999) or ACERBI AND TASCHE (2002)
[5] See for instance, the Swiss Solvency Test (e.g. WHITE PAPER ON SST (2004)).
[6] See TASCHE (2002), ALBRECHT (2003), ACERBI (2004), GRÜNDL AND WINTER (2005), MCNEIL, FREY AND EMBRECHTS (2006), LANGMANN (2005)
[7] STRASSBURGER (2006)
[8] See the discussion in EMBRECHTS, MCNEIL AND STRAUMANN (2002) and in MCNEIL, FREY AND EMBRECHTS (2006).
[9] Numerous illustrations of this problem can be found in LANGMANN (2005).

general results in underestimation of risk[10]. Thus, the VaR does not address the question of "how bad is bad"[11]. Another disadvantage is the absence of continuity in the VaR measure with respect to the confidence level – it may happen that for slightly different confidence levels one obtains considerably different values of the VaR[12].

In contrast to the VaR, our second considered risk measure the Expected Shortfall (ES) posses the property of sub-additivity, which is an important advantage due to the proper representation of the risk diversification principle[13]. In the pertinent literature, the ES is also often known as *Conditional Value at Risk (CVaR)*, *Tail Value at Risk (TVaR)* or *Average Value at Risk* – all of which refer to the same risk measure.

Beside the sub-additivity, another key advantage of the ES over the VaR measure is that the ES answers the question "how bad is bad" as it not only describes but also quantifies the fact of insolvency. Furthermore, the ES is continuous with respect to the confidence level as little modifications of confidence level result in commensurately small resulting changes of its value.

The ES measure is not without flaws though. It only reflects losses above the chosen confidence level and therefore is "sensitive mainly to extreme events"[14]. The ES will react sensitively to an adjustment of probabilistic distributions in the tail zone, which poses a problem as often there is no sufficient data for extreme events to clearly define the shape of the tail. Therefore, the effectiveness of the ES depends on the stability of estimates for probabilistic distributions. This is particularly the case for low-frequency and high-severity risks (e.g. natural hazards) and risks with unknown dependence structures.[15] All the above mentioned limitations may lead to significant estimation errors in applying the Expected Shortfall as a risk measure. Furthermore, there has been some criticism on the fact that pretending to cover the whole tail, the Expected Shortfall calculates only an expected value (in practice, an average) of all "worst" losses, hence ignoring the fact that every unlikely event will happen sooner or later given enough time[16]. Therefore, even though the ES provides more conservative estimates of the RBC for a given portfolio of risk than the VAR (e.g. specifically for catastrophic events with longer return periods), the real life portfolio losses will eventually exceed the ES projections as well. Nevertheless, as we discuss below, despite the above mentioned limitations, the ES measure of portfolio risk is perhaps one of the best currently available to insurance practioners for the purposes of determining the RBC requirements for highly volatile business lines with a high risk exposure in the tail of the probabilistic distribution.

[10] (e.g. ACERBI (2004), page 155 f., ARTZNER et al. (2002), page 169, KORYCIORZ (2004), page 70, LANGMANN (2005), page 36 ff.).
[11] (ARTZNER et al. (2002), page 169 or DHAENE et al. (2004), page 5)
[12] STRASSBURGER (2006).
[13] ACERBI AND TASCHE (2002)
[14] MEYERS (2002), page 15.
[15] WANG (2001), page 4.
[16] ROOTZÉN AND KLÜPPELBERG, 1999, page 5.

Sensitivity of Risk-Based Solvency Estimates to Data and Assumptions

In this Section we demonstrate the sensitivity of different risk-based solvency measures to correlation assumptions, treatment of extreme data points and the chosen levels of confidence for the computations[17]. This exercise is reduced to thirteen different but rather common scenarios demonstrating the sensitivity of risk-based solvency measures to data and model uncertainty for the same portfolio of catastrophe insurance risk. We demonstrate that each of these scenarios produces different, often highly diverging values of the RBC. A description of the actuarial work done for this purpose follows.

Event data set

To carry out our analyses, we used a stochastic data set of insured property losses in South East Europe. The data was provided by RMSI (2008), a risk modeling consultancy. The data set approximates losses that would be sustained by an insurance portfolio consisting exclusively of earthquake risk related liabilities, e.g. a portfolio of stand-alone earthquake insurance covers for residential property in four countries – Croatia, Bosnia and Herzegovina, Macedonia and Albania. A deductible of 3 percent was assumed for each insured loss. For each country, the RMSI provided an estimate of insured residential loss in the capital city and in the rest of country. Insurance penetration was assumed to be 8 percent in capital cities and 6 percent outside. The probability of occurrence for each loss event and its severity were estimated by RMSI based on the underlying physical hazard and building vulnerability data.

We assumed that the event frequency is distributed according to the Poisson distribution. From the original event data set described above, we derived the expected frequency (Poisson lambda) of 1.79. A customized distribution for loss severity results directly from the original event data set. Through a Monte-Carlo simulation for these frequency-severity parameters, we produced 100,000 data records of annual residential earthquake insured losses. Our sensitivity analysis was based on this derived data set. The data set specifies both (i) the total annual loss for the total residential portfolio in four countries and (ii) the total annual loss for each country separately. Further, for each country the loss in the capital city and outside is specified. Each of the 100,000 annual insured losses can occur with the entry probability of 1/100,000 = 0.001 percent.

Measures of required solvency capital

For the above described portfolio of insurance risk we performed the calculations of required solvency capital for each of three most common solvency capital measures: Solvency I, Solvency II and the Swiss Solvency Test (SST). Although the Solvency I measure cannot be viewed as a true risk-based measure of solvency, as we demonstrate below under certain circumstances it can

[17] Following the regulatory definitions of VAR and ES under the Solvency II and Swiss Solvency Test approaches, we define the confidence levels for these solvency measures at 99.5 and 99 percent, respectively.

exhibit some mild properties of a risk-based capital measure. For this reason and for the sake of analytical completeness the Solvency I measure is included in our analysis. The mathematical formulas used for these calculations are described below.

Solvency I

Required Solvency Capital = max (Premium Index, Claims Index)

Premium Index =
Retention Rate * (0.18 * min (Gross Premium, €50m) + 0.16 * max (Gross Premium - €50m, 0))

Claims Index =
Retention Rate * (+ 0.26 * min (Mean Gross Loss last 3 yrs, €35m)+ 0.23 * max (Mean Gross Loss last 3 yrs - €35m, 0))

Where

Retention Rate = Total Retained Loss for last 3 yrs / Total Gross Loss for last 3 yrs

Gross Premium = + Expected Annual Loss + RoRaC + Admin Expenses

Where RoRaC denotes Return on Risk Adjusted Capital and is calculated as follows

RoRaC = Risk Adjusted Capital * Target Rate of Return

The Target Rate of Return was chosen to be 15 percent. The Risk Adjusted Capital was calculated as

Risk Adjusted Capital = + Annual Loss VaR (99.5%) – Expected Annual Loss

Hence,

RoRaC = (+ Annual Loss VaR (99.5%) – Expected Annual Loss) *15%

Please notice that for the Risk Adjusted Capital was chosen for the confidence level of 99.5%, which is in line with the most common industry practice and regulatory requirements for investment-grade rated insurance companies. However, other choices are also possible depending on the company's rating and solvency requirements, the extent of risk aversion, and the quality of risk management.

Finally, we assumed the Administrative Expenses to be 10 percent of Gross Premium Written.

Admin Expenses = 10% of Gross Premium

Further, we assumed

(i) Retention Ratio = 1 (no reinsurance)
(ii) Claims Index = 0 (no claims for last 3 yrs)

With the hindsight of the formula for the Required Solvency capital under the Solvency II (see below), we can then rewrite the above presented RaRoC formula for Solvency I as follows:

RoRaC =(Required Solvency Capital II) *15%,

where Required Solvency Capital II denotes the Required Solvency Capital under the Solvency II.
By substituting RoRaC with the above produced right side of equation, we can then rewrite the formula for Gross Premium as follows:

GP = Expected Loss + 15% *(Required Solvency Capital II) + Admin Expenses

The Solvency I premium-based formula can then be rewritten as follows:

Premium Index =
Retention Rate * ((0.18 * min (Expected Loss + 15% *(Required Solvency Capital II) + Admin Expenses), €50m) + 0.16 * max ((Expected Loss + 15% *(Required Solvency Capital II) + Admin Expenses), - €50m, 0))

By expressing the premium-based index of Solvency I in terms of Solvency II, we have turned it into a risk-based capital measure. The problem with the Solvency I measure however is that it accounts only for a very small fraction of Solvency II capital requirements, which can be traced throughout our modeling scenarios below.

Solvency II

Required Solvency Capital = + Annual Loss VaR (99.5%) – Expected Annual Loss

where Annual Loss VaR (99.5%) denotes the annual VAR for the confidence level of 99.5 percent - the 99.5 percentile of the annual loss distribution or the value of the annual loss which, with probability of 99.5%, will not be exceeded. This value can be estimated directly from the annual loss data as described above.

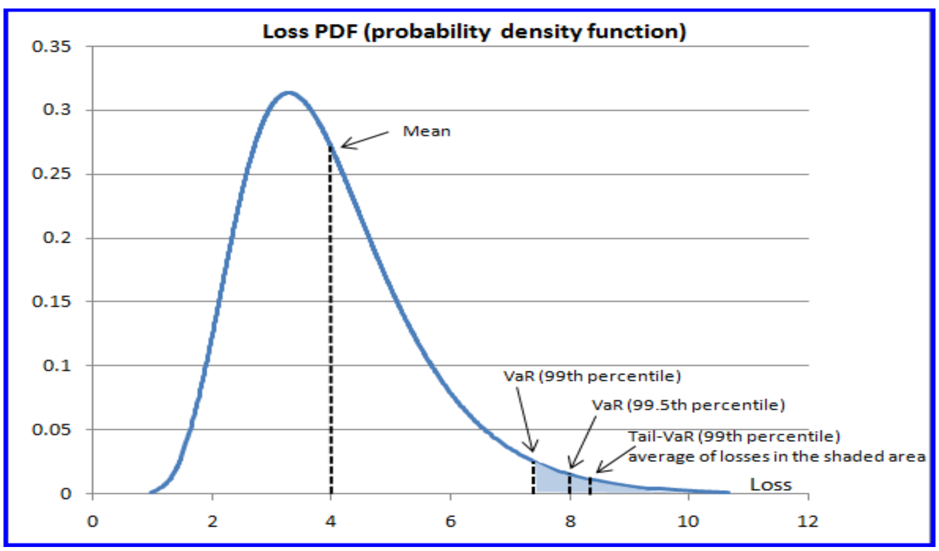
Swiss Solvency Test

Required Solvency Capital = + Annual Loss TVaR(99.0%) - Expected Annual Loss

where Annual Loss TVaR (99.0%) denotes the Annual Loss Tail Value at Risk (also often called the Expected Shortfall) at the confidence level of 99.0 percent. This is the average annual loss calculated from the data set values that exceed those in excess of 99.0 percentile of the annual loss distribution. In other words, it's an average calculated for the losses from the data set which can only be exceeded with probabilities lower than 1.0 percent. To put it differently, TVaR is the risk measure which approximates the whole tail of the distribution whereas VaR looks at losses up to a predefined percentile, thus disregarding the tail of distributions.

In Figure 1, we provide an graphic illustration of the differences among the above described measures of RBC.

Figure 1



Return on Equity

For the purposes of this paper, we assumed that the required solvency capital is financed by shareholders' equity. Usually, company's shareholders would require some adequate return on their investment in the company, which we assumed to be 15 percent. Then the Required Return on Equity (RoE) can be calculated as follows:

Required RoE = Solvency Capital * Required Rate of Return on Equity

Notice that one would obtain different RoEs for different solvency capital calculation frameworks.

Sensitivity Analysis

The objective of the sensitivity analysis is to investigate the sensitivity of the risk-based solvency requirements as well as the RoE to the uncertainties in the underlying stochastic model for the annual insured loss.

To assess this sensitivity, we first considered several different realistic data uncertainty scenarios. Each of these scenarios differs in some way from the original ("benchmark") modeling scenario used to calculate the annual insured loss for the above presented measures of the risk. As a result, each scenario generates an annual maximum loss estimate which incorporates the corresponding uncertainty of the data. We then calculated the required solvency capital and RoE for each of the scenarios and compared them with the ones calculated for the original annual insured loss model.

All in all, we have considered the following 15 data uncertainty scenarios, including the original "benchmark" scenario and a subset of Scenario 8. A brief description of the selected scenarios and produced results follows[18]:

Scenario 0 ("Benchmark")
Takes all loss values in the stochastic data set as is for the purposes of calculating solvency measures.

	Required Solvency Capital	Required RoE
Solvency I	8,139,722.94	1,220,958.44
Solvency II	202,952,499.20	30,442,874.88
Swiss Solvency Test	216,493,498.73	32,474,024.81

[18] See Aanex I for the results of all scenarios.

The first clear observation one can make from the benchmark scenario is that a very significant gap exists between the estimates of solvency obtained through the existing and most commonly applied Solvency I regime and those obtained by applying the risk-based solvency measures (e.g. Solvency II and Swiss Solvency Test). The second observation demonstrates that the Swiss Solvency Test is a more conservative (to the tune of 15 percent) estimate of risk than Solvency II. Finally, one can clearly see that due to a huge difference in solvency capital requirements mandated by different solvency regimes, an insurer with a portfolio of catastrophic risk would receive a significant boost to its bottom line simply by staying with the Solvency I regime.

Scenario 1

Drops the largest single loss from 100,000 annual losses in the model.

	Solvency Capital	Delta to orig. event set	RoE	Delta to orig. event set	Delta RoE abs
Solvency I	8,133,534.23	-0.08%	1,220,030.13	-0.08%	-928.31
Solvency II	202,780,919	-0.08%	30,417,137	-0.08%	-25,736
Swiss Solvency Test	216,132,656	-0.17%	32,419,898	-0.17%	-54,126

As can be seen from the table, by eliminating the largest single outlier in the data series we have achieved almost no effect on the risk-based solvency measures.

Scenario 2

Drops two largest loses out of 100,000 annual losses in the model (e.g., annual losses above the return period of 50,000 yrs).

	Solvency Capital	Delta to orig. event set	RoE	Delta to orig event set	Delta RoE abs
Solvency I	8,101,527.67	-0.47%	1,215,229.15	-0.47%	-5,729.29
Solvency II	201,745,962	-0.59%	30,261,894	-0.59%	-180,980
Swiss Solvency Test	215,813,117	-0.31%	32,371,967	-0.31%	-102,057

Similar to Scenario 2, by dropping 2 largest annual losses from the data set we have observed only a slight decline (well under 1 percent) in the estimates of solvency capital for all three measures.

Scenario 6

Drops ten largest losses out of 100,000 annual losses in the model (annual losses above the return period of 10,000 yrs).

	Solvency Capital	Delta to orig. event set	RoE	Delta to orig. event set	Delta RoE abs

Solvency I	8,046,913.55	-1.14%	1,207,037.03	-1.14%	-13,921.41
Solvency II	200,155,238	-1.38%	30,023,285	-1.38%	-419,589
Swiss Solvency Test	213,635,878	-1.32%	32,045,381	-1.32%	-428,643

As can be seen from the table above, the two measures of risk-based solvency react almost similar to the omission of 10 largest losses from the distribution (-1.38 and -1.32 percent, respectively).

Scenario 9

Drops hundred largest losses out of 100,000 annual losses in the model (annual losses above the return period of 1,000 yrs).

	Solvency Capital	Delta to orig. event set	RoE	Delta to orig. event set	Delta RoE abs
Solvency I	7,541,847.08	-7.35%	1,131,277.06	-7.35%	-89,681.38
Solvency II	185,418,312	-8.64%	27,812,746	-8.64%	-2,630,127
Swiss Solvency Test	196,072,237	-9.43%	29,410,835	-9.43%	-3,063,189

Scenario 9 demonstrates however that ultimately the quantity translates into quality – all three measures of solvency have shown about same reaction to the elimination of 100 largest loss events from the data set, by registering a drop of -7.35, -8.64 and -9.43 percent for Solvency I, Solvency II and Swiss Solvency Test, respectively. In the case of our risk portfolio, it means that by eliminating all losses in the data series in excess of 1000 year return period, which in our case amounts to only 0.1 percent of all loss events, an insurer can reduce its required solvency capital by about 10 percent. The simulation also shows that the Swiss Solvency Test is the most sensitive to this change.

Scenario 10

In this scenario, we error on the conservative side by introducing a 30 percent upward adjustment of losses occurring from events with a return period in excess of 1000 years. The scenario effectively tries to compensate for considerable uncertainty involved in modeling losses from events with such long return periods.

	Solvency Capital	Delta to orig. event set	RoE	Delta to orig. event set	Delta RoE abs
Solvency I	8,158,044.76	0.23%	1,223,706.71	0.23%	2,748.27
Solvency II	202,844,723	-0.05%	30,426,708	-0.05%	-16,166
Swiss Solvency Test	227,163,262	4.93%	34,074,489	4.93%	1,600,464

The outcomes of this simulation by and large conform with the criticism of the VAR based measures of risk capital discussed in the introduction to this paper. As can be seen from the result table for this scenario, despite the appearance of a noticeably heavier tail in the underlying loss distribution, Solvency II estimate of solvency remains virtually the same. At the same time, the TVAR based-measure of risk has shown a considerable sensitivity to this adjustment by increasing by about 5 percent. A slight change in the Solvency I capital requirement can be attributed to the increase in gross premium (stemming from increased standard deviation), which in the absence of losses over the last 3 years, is used as a basis for calculating the solvency requirement.

Scenario 12

Introduces a 100 percent upward adjustment for losses with a return period of 1000 years.

	Solvency Capital	Delta to orig. event set	RoE	Delta to orig event set	Delta RoE abs
Solvency I	8,200,795.66	0.75%	1,230,119.35	0.75%	9,160.91
Solvency II	202,593,247	-0.18%	30,388,987	-0.18%	-53,887
Swiss Solvency Test	252,059,378	16.43%	37,808,906	16.43%	5,334,882

The results presented in the table only confirm our previous conclusion about the lack of sensitivity of VAR type measures as well as the Solvency I index to across the board changes in the tail of risk distributions and at the same time a considerable sensitivity of TVAR measures to the tail risk. The differences are quite illustrative – when the TVAR goes up by 16.43 percent the values of Solvency I and II measures remains almost same.

Scenario 14

Disregards correlations between annual losses in eight sub-portfolios corresponding to capital city and rest or country for each county under consideration.

	Solvency Capital	Delta to orig. event set	RoE	Delta to orig. event set	Delta RoE abs
Solvency I	5,982,594.31	-26.50%	897,389.15	-26.50%	-323,569.29
Solvency II	131,048,211	-35.43%	19,657,231	-35.43%	-10,785,643
Swiss Solvency Test	146,867,953	-32.16%	22,030,193	-32.16%	-10,443,831

In this scenario, an insurer disregards correlations that may exist between different sub-portfolios of risk in its aggregate portfolio – a scenario quite typical for many insurance entities involved in underwriting catastrophe risk often without sufficient information about potential risk accumulations. It is interesting to observe that in this case all three measures of solvency drop by approximately the same amount – about 30 percent.

Conclusions

Based on the above presented sensitivity analysis we can make several important observations.

When utilizing Solvency I and Solvency II measures, the regulators should be mindful of the fact that these measures are inherently (e.g. by their design) insensitive to the risk exposure in the tail of abnormal risk distributions and hence can be rather misleading if used to determine the solvency requirements for insurance-based entities involved in underwriting volatile classes of insurance risk with a substantial exposure in the tail of the distribution (e.g. marine, aviation, commercial liability and natural disasters.
The Swiss Solvency Test is the measure of risk-based solvency best suited for "tail dominated" business lines due to its considerable sensitivity to risk exposure in the tail of abnormal distributions.

1. Regulators however should be aware of the Swiss Solvency Test limitations. Our computational work demonstrates that the TVAR based approaches to determining insurers' solvency requirements should be used with caution due to its considerable sensitivity to modeling uncertainties in the tail of abnormal distributions, as we have shown in the scenarios 9, 10, 11, and 12. In practical terms, by requiring TVAR based measures in the absence of proper oversight, the regulators may create ample space for potential data manipulation in cases when insurers are under pressure to reduce their capital costs. In modeling natural hazards, uncertainties of this type and range are quite typical for return periods of 200 year or longer.

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The VaR based Solvency II measure shows substantially lower sensitivity to model and data uncertainties in the tail of the distribution in scenarios that increase the weight of the distribution tail, as demonstrated by scenarios 10, 11, 12 that. However, in the cases where we have eliminated the data outliers in excess of a 200-year return period the Solvency II measure has also shown substantial sensitivity due to a shift of the whole distribution to the left, as is in Scenario 9. We therefore conclude that while being reasonably sensitive to the reduced uncertainty, the Solvency II measure equally fails to record increased uncertainty in the long-run.

We also show a very significant impact of correlation assumptions on all three measures of solvency, which underscores the importance of accumulation control procedures and up-to-date information about correlation between different risks in insurers‘ portfolios.

2. Finally, the empirical analysis shows a considerable actuarial discretion allowed by different measures of solvency and assumptions that go into them, which is particularly the case for the Swiss Solvency Test. We demonstrate that the material financial outcomes of such actuarial discretion in calculating the insurer's solvency may invite management and shareholders' pressure to reduce the estimates of RBC for a given risk portfolio. In the extreme cases, the choice of the RBC measure and of modeling approach can either add or subtract millions of dollars to/from the company's bottom line. Given the prevailing structure of management compensation and short-term profit maximizing incentives of shareholders in most public insurance companies, this finding not only underscores the importance of the actuarial profession, but also raises the question about its professional independence and ability to effectively resist pressure from the management and shareholders whose myopic bottom-line objectives may be at odds with the goal of achieving long-term solvency[19].

Policy Recommendations

Based on the above presented conclusions we would like to make the following three recommendations:

1. Given the inherent lack of sensitivity of the Solvency II measure to the risk exposure in the tail of abnormal distributions, regulators may consider supplementing it with other risk-based solvency measures (e.g. such as TVaR) when it comes to determining solvency requirements for insurance entities with heavy exposure to volatile "tail dominated" business lines (e.g. aviation, marine, mortgage insurers, natcat and commercial liability).

This recommendation however should not be interpreted as an argument for using instead of the VaR the expected shortfall based approaches (TVAR), as the latter suffer from considerable sensitivity to modeling uncertainties in the tail of abnormal distributions.

2. Due to the sensitivity of the risk-based solvency measures (e.g. mainly TVaR and less so VaR) to underlying data and modeling assumptions in determining the risk-based solvency, insurance regulators may consider requiring their full disclosure. To avoid potential misuse of modeling and data uncertainties by some insurance entities in calculating the RBC requirements, it may be advisable to establish standard universal modeling and data quality and verification requirements for the most critical building blocks of the risk modeling process (e.g. the loss return period, treatment of outliers beyond the given return period threshold, suggested shape of the tail in abnormal distributions in the absence of sufficient

[19] For a comprehensive discussion of management incentives to take excessive risks in a highly leveraged liability business see "Regulating Bankers' Pay" by Lucian Bebchuk and Holger Spamann, Harvard Law and Economics Discussion Paper No. 641, 2009.

data, as well as correlation assumptions used to model individual classes of risk as well as aggregate portfolios).

3. We also would like to recommend strengthening the independence of actuaries from potential management pressures to adjust the estimates of risk-based capital downwards for the sake of short-term profitability. This can be achieved by requiring companies to subject their estimates to external actuarial audits as well as to introduce standard solvency estimation models approved by the insurance regulators.

   Insurers disagreeing with the estimates of their risk-based solvency produced by such standard models should then be able to justify to the regulator (which would require a modeling audit by an independent modeling provider) why their own custom-tailored solvency model is superior to that proposed by the regulator for the entire market.

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ANNEX I

Complete list of Solvency Sensitivity Tests

Scenario 1
Drop the largest loss of 100,000 annual losses in the model

Scenario 2
Drop two largest losses of 100,000 annual losses in the model (annual losses above the return period of 50,000 yrs)

Scenario 3
Drop three largest losses of 100,000 annual losses in the model (annual losses above the return period of 33,000 yrs)

Scenario 4
Drop four largest losses of 100,000 annual losses in the model (annual losses above the return period of 25,000 yrs)

Scenario 5
Drop five largest losses of 100,000 annual losses in the model (annual losses above the return period of 20,000 yrs)

Scenario 6
Drop ten largest losses of 100,000 annual losses in the model (annual losses above the return period of 10,000 yrs)

Scenario 7
Drop fifteen largest losses of 100,000 annual losses in the model (annual losses above the return period of 7,000 yrs)

Scenario 8
Drop twenty largest losses of 100,000 annual losses in the model (annual losses above the return period of 5,000 yrs)

Scenario 9
Drop hundred largest losses of 100,000 annual losses in the model (annual losses above the return period of 1,000 yrs)

Scenario 10

Underestimate of annual losses with return periods above 1000yrs in the original model. 30% adjustment of these losses is required.

Scenario 11

Underestimate of annual losses with return periods above 1000yrs in the original model. 50% adjustment of these losses is required.

Scenario 12

Underestimate of annual losses with return periods above 1000yrs in the original model. 100% adjustment of these losses is required.

Scenario 13

Disregard correlation between annual losses in four sub-portfolios corresponding to four countries under consideration.

Scenario 14

Disregard correlation between annual losses in eight sub-portfolios corresponding to capital city and rest or country for each county under consideation.

Following results were obtained

Original Model

	Solvency Capital	RoE
Solvency I	8,139,722.94	1,220,958.44
Solvency II	202,952,499.20	30,442,874.88
Swiss Solvency Test	216,493,498.73	32,474,024.81

Scenario 1

	Solvency Capital	Delta to orig event set	**RoE**	Delta to orig event set	Delta RoE abs
Solvency I	8,133,534.23	-0.08%	1,220,030.13	-0.08%	-928.31
Solvency II	202,780,919.69	-0.08%	30,417,137.95	-0.08%	-25,736.93
Swiss Solvency Test	216,132,656.83	-0.17%	32,419,898.52	-0.17%	-54,126.29

Scenario 2

	Solvency Capital	Delta to orig event set	RoE	Delta to orig event set	Delta RoE abs
Solvency I	8,101,527.67	-0.47%	1,215,229.15	-0.47%	-5,729.29
Solvency II	201,745,962.29	-0.59%	30,261,894.34	-0.59%	-180,980.54
Swiss Solvency Test	215,813,117.00	-0.31%	32,371,967.55	-0.31%	-102,057.26

Scenario 3

	Solvency Capital	Delta to orig event set	RoE	Delta to orig event set	Delta RoE abs
Solvency I	8,097,918.30	-0.51%	1,214,687.75	-0.51%	-6,270.70
Solvency II	201,655,771.50	-0.64%	30,248,365.72	-0.64%	-194,509.15
Swiss Solvency Test	215,520,385.85	-0.45%	32,328,057.88	-0.45%	-145,966.93

Scenario 4

	Solvency Capital	Delta to orig event set	RoE	Delta to orig event set	Delta RoE abs
Solvency I	8,083,386.27	-0.69%	1,212,507.94	-0.69%	-8,450.50
Solvency II	201,201,331.01	-0.86%	30,180,199.65	-0.86%	-262,675.23
Swiss Solvency Test	215,230,036.28	-0.58%	32,284,505.44	-0.58%	-189,519.37

Scenario 5

	Solvency Capital	Delta to orig event set	RoE	Delta to orig event set	Delta RoE abs
Solvency I	8,081,955.98	-0.71%	1,212,293.40	-0.71%	-8,665.04
Solvency II	201,182,647.41	-0.87%	30,177,397.11	-0.87%	-265,477.77
Swiss Solvency Test	214,953,992.68	-0.71%	32,243,098.90	-0.71%	-230,925.91

Scenario 6

	Solvency Capital	Delta to orig event set	RoE	Delta to orig event set	Delta RoE abs
Solvency I	8,046,913.55	-1.14%	1,207,037.03	-1.14%	-13,921.41
Solvency II	200,155,238.85	-1.38%	30,023,285.83	-1.38%	-419,589.05
Swiss Solvency Test	213,635,878.49	-1.32%	32,045,381.77	-1.32%	-428,643.04

Scenario 7

	Solvency Capital	Delta to orig event set	RoE	Delta to orig event set	Delta RoE abs
Solvency I	8,005,048.94	-1.65%	1,200,757.34	-1.65%	-20,201.10
Solvency II	198,890,030.89	-2.00%	29,833,504.63	-2.00%	-609,370.25
Swiss Solvency Test	212,677,587.49	-1.76%	31,901,638.12	-1.76%	-572,386.69

Scenario 8

	Solvency Capital	Delta to orig event set	RoE	Delta to orig event set	Delta RoE abs
Solvency I	7,971,196.92	-2.07%	1,195,679.54	-2.07%	-25,278.90
Solvency II	197,888,232.03	-2.50%	29,683,234.80	-2.50%	-759,640.07
Swiss Solvency Test	211,358,070.87	-2.37%	31,703,710.63	-2.37%	-770,314.18

Scenario 9

	Solvency Capital	Delta to orig event set	RoE	Delta to orig event set	Delta RoE abs
Solvency I	7,541,847.08	-7.35%	1,131,277.06	-7.35%	-89,681.38
Solvency II	185,418,312.81	-8.64%	27,812,746.92	-8.64%	-2,630,127.96

Swiss Solvency Test	196,072,237.73	-9.43%	29,410,835.66	-9.43%	-3,063,189.15

Scenario 10

	Solvency Capital	Delta to orig event set	RoE	Delta to orig event set	Delta RoE abs
Solvency I	8,158,044.76	0.23%	1,223,706.71	0.23%	2,748.27
Solvency II	202,844,723.80	-0.05%	30,426,708.57	-0.05%	-16,166.31
Swiss Solvency Test	227,163,262.78	4.93%	34,074,489.42	4.93%	1,600,464.61

Scenario 11

	Solvency Capital	Delta to orig event set	RoE	Delta to orig event set	Delta RoE abs
Solvency I	8,170,259.30	0.38%	1,225,538.89	0.38%	4,580.45
Solvency II	202,772,873.54	-0.09%	30,415,931.03	-0.09%	-26,943.85
Swiss Solvency Test	234,276,438.81	8.21%	35,141,465.82	8.21%	2,667,441.01

Scenario 12

	Solvency Capital	Delta to orig event set	RoE	Delta to orig event set	Delta RoE abs
Solvency I	8,200,795.66	0.75%	1,230,119.35	0.75%	9,160.91
Solvency II	202,593,247.88	-0.18%	30,388,987.18	-0.18%	-53,887.70
Swiss Solvency Test	252,059,378.88	16.43%	37,808,906.83	16.43%	5,334,882.02

Scenario 13

	Solvency Capital	Delta to orig event set	RoE	Delta to orig event set	Delta RoE abs
Solvency I	8,054,991.29	-1.04%	1,208,248.69	-1.04%	-12,709.75
Solvency II	200,128,110.95	-1.39%	30,019,216.64	-1.39%	-423,658.24
Swiss Solvency Test	213,953,653.42	-1.17%	32,093,048.01	-1.17%	-380,976.80

Scenario 14

	Solvency Capital	Delta to orig event set	RoE	Delta to orig event set	Delta RoE abs
Solvency I	5,982,594.31	-26.50%	897,389.15	-26.50%	-323,569.29
Solvency II	131,048,211.53	-35.43%	19,657,231.73	-35.43%	-10,785,643.15
Swiss Solvency Test	146,867,953.30	-32.16%	22,030,193.00	-32.16%	-10,443,831.81