# Discretionary Decisions in Capital Requirements under Solvency II

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**Abstract**

European insurers are allowed to make discretionary decisions in the calculation of Solvency II capital requirements. These choices include the design of risk models (ranging from a standard formula to a full internal model) and the use of long-term guarantees measures. This article examines the impact and the drivers of discretionary decisions with respect to capital requirements for market risks. In a first step of our analysis, we assess the risk profiles of 49 stock insurers using daily market data. In a second step, we exploit hand-collected Solvency II data for the years 2016 to 2020. We find that long-term guarantees measures substantially influence the reported solvency ratios. The measures are chosen particularly by less solvent insurers and firms with high interest rate and credit spread sensitivities. Internal models are used more frequently by large insurers and especially for risks for which the firms have already found adequate immunization strategies.

**Keywords**: Solvency II, capital requirements, discretionary decisions

**JEL Classification**: G22, G28, G32

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# 1 Introduction

Modern regulatory frameworks for financial institutions aim to provide a fair view of the risk and solvency situation of regulated entities. Solvency II, introduced in 2016 for insurance companies in the European Economic Area (EEA), was one of the first frameworks that aimed to accurately measure the solvency of insurers, taking into account multiple risk categories and diversification effects. Similar to banking regulation under the Basel Capital Accord, Solvency II does not define a unique method for quantifying risk, but instead allows insurers to choose among options. One important option is to choose between a standardized and an internal approach to calculating capital requirements. For banks, this set-up with two alternatives has been the subject of considerable criticism. Since the initial implementation of the internal approach is costly for banks, only large financial institutions are effectively in a position to choose such an approach and thereby gain a competitive advantage. The option may thus create moral hazard problems and increase the aggregate risk in the economy (cf. Hakenes and Schnabel (2011)). Moreover, empirical evidence suggests that banks deliberately choose and calibrate their risk models in such a way that their reported risk situation brightens up (cf. Colliard (2019), Plosser and Santos (2014)).

Compared to the Basel Capital Accord, Solvency II offers insurers a much wider range of implementation options. The first pillar of Solvency II defines a market-oriented balance sheet approach to measure insurers' own funds and a risk-based approach to determine their Solvency Capital Requirement (SCR). The SCR is intended to reflect the loss of an insurer's own funds over a 1-year time horizon in a 1-in-200 year event due to various risks, including market, credit and underwriting risks. To calculate the SCR, insurers can use a proprietary full internal model that covers the entire risk landscape, or a standard formula defined by the regulator. As a further option, they can use a partial internal model, which means that they select the risk categories that they model internally and use the standard formula for the others. In addition, there are four non-mandatory long-term guarantees (LTG) measures that insurers may or may not use (cf. Articles 43-54, European Commission (2015)): matching adjustment, volatility adjustment, transitional measure on the risk-free interest rates, and transitional measure on technical provision. These measures affect the discount rate that insurers use to calculate their technical provisions and have a direct impact on the calculation of SCR and the insurers' own funds.

There is a substantial variety in the way that insurers choose to determine their own funds and SCR. In 2020, 651 out of 2458 companies used at least one LTG measure, 91 employed a partial internal model, and 56 used a full internal model (cf. European Insurance and Occupational

Pensions Authority (EIOPA) (2020)). Both LTG measures and the use of internal models are positively associated with the insurer size.[1] At the same time, the instruments have a substantial impact on the solvency ratio, which is the ratio of the insurers' own funds to SCR and is frequently employed to express the financial soundness in a single figure (cf. Mukhtarov et al. (2022)). For instance, the average solvency ratio of insurers using at least one LTG would fall from 247% to 204% if this instrument were removed (cf. EIOPA (2020)).

The purpose of this paper is to investigate the determinants of insurers' discretionary decisions in the implementation of Solvency II. Specifically, we aim to shed light on the relationship between information about insurers' risk profiles and their implementation strategy. We suspect that insurers strategically make use of the leeway in determining the solvency ratio. When deciding on LTG measures and internal models, they weigh the advantages and disadvantages. While LTGs can improve an insurer's reported solvency ratio, they involve increased disclosure requirements and regulatory attention, as local regulators closely monitor their use. The trade-off may depend on an insurer's risk profile. For instance, the volatility adjustment enhances an insurer's solvency ratio more effectively the higher its interest rate risk is. Internal models tend to measure risks more accurately than the standard formula, for which systematic biases in the measurement of market risk and default risk have been identified (cf. Fischer and Schlütter (2015), Braun et al. (2017), Asadi and Al Janabi (2020)). On the one hand, internal models can be advantageous as a basis for decision-making, because they more accurately assess the impact of strategic options on the risk profile. On the other hand, the development and operation of the models is complex and costly, especially as the models have to comply with regulatory requirements. The impact of an internal model on the solvency ratio is ambiguous, as the standard formula is partly built with safety buffers, but some risks cannot be covered by capital.

Previous studies examining the risk profiles of insurers find that market risks are typically the biggest threat to the solvency of life insurance companies, mainly due to the long duration of their liabilities and a high proportion of investments in government bonds (cf. Duverne and Hele (2017), Frey (2012), EIOPA (2017a)). Several empirical studies have measured the exposure of insurers to changes in long-term interest rates (e.g., Brewer et al. (2007), Carson et al. (2008) and Möhlmann (2021)). For instance, Hartley et al. (2017) show that insurers benefitted significantly from rising long-term interest rates in the low interest rate environment following the financial crisis. Moreover, Düll et al. (2017) reveal that insurers are significantly

[1] Insurers using at least one LTG measure hold 80% of the technical provisions of all insurers subject to Solvency II (cf. EIOPA (2020)).

affected by changes in credit default swap (CDS) spreads on government bonds. Grochola et al. (2023) point out that sovereign credit risk is of relatively high importance for European insurers compared to U.S. insurers, whose risk profile is dominated by interest rate risk.

To answer our research question, we proceed in two steps. First, we analyze how the market capitalization of 49 listed insurers from 15 European countries reacts to long-term interest rate movements, CDS spread changes and a stock market index.[2] We perform insurer-level multivariate regression analyses based on daily market data to identify insurers' interest rate risk, credit risk and stock market sensitivities (measured by the beta coefficients). The results of examining the risk profiles are largely consistent with other empirical studies.

Second, we systematically gathered information on insurers' discretionary decisions and risk management approaches from the Solvency and Financial Condition Reports (SFCRs) that European insurers are required to publish annually.[3] We obtained data on the solvency ratio and the impact of the LTG measures as well as qualitative information on the composition of internal models. To this end, we examined the reports of 49 insurers in the sample from the introduction of Solvency II in 2016 up until 2020. We then examined which market risk sensitivities and insurer characteristics, such as size and share of life business, are most helpful in explaining insurers' decisions regarding the use of LTG measures and internal models.

The idea behind the SFCRs is that insurers' stakeholders gain transparency on their risk profiles and that their potential reaction provides insurers with an incentive to seek a sound risk and solvency position. From a stakeholder perspective, it is important to have empirical evidence on whether the reported solvency ratio is meaningful and whether this regulatory tool works. Gatzert and Heidinger (2020) and Mukhtarov et al. (2022) show that the published quantitative data on risk characteristics lead to a significant abnormal stock return, suggesting that shareholders react to the news provided by SFCRs. However, it remains an open question concerning the extent to which the reported solvency ratios reflect the insurers' true risk profiles.

For the insurers in our sample, the results show that the solvency ratios are strongly affected by the LTG measures. First, the volatility adjustment was applied by 69% of insurers in 2020 and has a significantly larger impact on the solvency ratio for otherwise less solvent insurers and for firms with high interest rate sensitivity, even when controlling for the share of life insurance

[2] Obtaining market risk sensitivities by running firm-level regressions using stock returns as the dependent variable is an approach that has been used by Berends et al. (2013) and Brewer et al. (2007) for insurers, and by Campbell et al. (2001) and Da et al. (2012) for a broader sample of firms.

[3] The SFCRs provide detailed information on the business, performance, governance system, risk profile, valuation for solvency purposes and capital management of insurers (cf. Articles 292-298, European Commission (2015)).

business. Second, the matching adjustment has the largest impact, increasing the solvency ratio by an average of 59 percentage points (ppt). Its impact is significantly more pronounced for large insurers and those with high sovereign credit risk. Third, the use of the transitional for technical provisions is driven by insurers' "true" solvency ratios and their exposure to interest rate risk. Overall, we find that LTG measures increase the reported solvency ratios by an average of 29ppt. Our findings suggest that insurers use LTGs strategically to exploit the flexibility offered by Solvency II in order to maximize the reported solvency ratio and to mask their market risk profiles. Discretionary decisions can thus cause Solvency II figures to deviate from a market-oriented, risk-based view of insurers' risk positions.

Regarding internal models, we find heterogeneity in their composition across European insurers. While only five insurance groups in our sample use full internal models in 2020, 19 have modeled the SCR market risk module internally. Logistic regressions show that the probability of using an internal model is higher for more solvent and larger insurers, and for those with lower exposure to sovereign credit risk. Since the interest rate submodule is also more likely to be modeled internally by insurers with lower interest rate risk, we assume that internal models are being adopted primarily for risks for which insurers have already found adequate immunization strategies. The spread and default risk of EU government bonds is only addressed by a few large insurers that receive considerable regulatory and public attention.

The remainder of the paper is structured as follows. The methodology for estimating market risk sensitivities is outlined in Section 2. Our approach and the empirical results addressing the research question on the drivers of discretionary decisions under Solvency II are presented in Section 3. Section 4 concludes the paper.

# 2 Estimation of market risk sensitivities

## 2.1 Dependent variable

Our sample consists of European insurers that are publicly listed and for which daily share price data can be obtained from Refinitiv. Additionally, we restrict our analysis to insurers that have published at least one Solvency and Financial Condition Report (SFCR) at the group level. We exclude from the sample five micro-cap insurers with less than $250 million in total assets at year-end 2020,[4] and three insurers due to low data frequency (less than 100 stock price observations per year), as the estimated insurer-level coefficients may be biased due to more

[4] Micro-cap firms have lower liquidity and potentially anomalous risk-return profiles compared to larger companies due to factors such as higher volatility and growth prospects (cf. Lins et al. (2017)). Our empirical results are robust to the inclusion of micro-cap insurers in the sample (cf. Table A5 in Appendix IV).

volatile, missing, or inaccurately timed observations. Therefore, a total of eight insurers are excluded, none of which used an LTG measure or internal model between 2016 and 2020.[5]

To conduct the empirical analysis of market risk sensitivities, we collected daily stock prices for 49 insurers across 15 European countries from 20 March 2006 to 30 December 2019, using Refinitiv as our data source. We chose this time frame to adequately reflect the performance of the insurers and then estimated their long-term risk profiles through sensitivities to market risk drivers. Our analysis covers a period of 3,775 trading days, during which we observed daily returns. The dependent variable in our regression model, $r_t$, is the relative daily change in the total return index (TRI), which captures stock prices after accounting for dividend payments and fluctuations in the number of shares outstanding. We use $r_t$ as a measure of stock returns.

$$r_t = \frac{TRI_t}{TRI_{t_{previous}}} - 1 \qquad (1)$$

If the TRI remains unchanged for at least three consecutive days, we assume missing data and exclude the TRI observation starting from the second day. Table 1 presents the descriptive statistics for the sum of all remaining stock price and stock return observations. The statistics of the collected stock returns $r_t$ at the insurer level are presented in Table A1 in Appendix I. They show that the mean of the daily stock returns ranges from -0.01% to 0.22% and the standard deviation from 1.21% to 4.05%. Outliers with absolute daily returns greater than 50% are removed from the regressions. In 2020, the total assets of all companies in our sample amount to €7.606 trillion (€5.274 trillion after excluding U.K. insurers), which represents about 57% of the assets of all insurers in the EEA based on data from EIOPA (2023).

## 2.2 Independent variables

To assess interest rate risk, we use 10-year interest rates from the European Central Bank (ECB). The data is sourced from daily estimates of the euro yield curve, with a term structure that is derived using the Svensson model applied to AAA-rated Euro area government bonds. The resulting annual interest rates represent those of a 10-year zero-coupon bond.

Following the methodology of Brewer et al. (2007) and Grochola et al. (2023), we use the holding period return (hpr) of long-term interest rates as the independent variable to measure interest rate risk. This return is equal to the return on a zero-coupon bond purchased at the prevailing interest rate and sold the next day. If the 10-year interest rate (denoted as $y10$) were

[5] The excluded companies are mostly from smaller European insurance markets: Cyprus (two insurers), Croatia (one), Hungary (one), Iceland (one), Malta (one). There is one insurer each from Norway and the U.K.

to rise in the meantime, the market value of the bond would fall, resulting in a negative hpr within one trading day. Thus, a positive hpr would only be observed after a decline in the interest rate. The calculation of the hpr on day $t$ is as follows:

$$r_{y10,t} = \left(\frac{1 + y10_{t_{previous}}}{1 + y10_t}\right)^{10} - 1 \quad (2)$$

Given that European insurers allocate a significant portion of their assets to sovereign debt, as evidenced by EIOPA (2016a), we use CDS spreads on government bonds as a proxy for credit risk. The data for CDS spreads are obtained from IHS Markit. Following the approach of Düll et al. (2017), we specifically select CDS spreads denominated in USD with a maturity of five years. These spreads reflect the estimated probability of a country defaulting on its payment obligations within five years of the issue date, and thus serve as an indicator of credit risk.

We collect sovereign CDS data for all countries in which the insurers in our sample are headquartered. Each insurer is assigned to the domestic CDS quotes based on its country of origin (denoted as $c$). Hence, we employ country-specific data as a measure of credit risk, distinguishing it from the other independent variables. We adopt this approach because insurers' sensitivities are significantly affected by domestic CDS spreads, as shown by Düll et al. (2017). For each day $t$, we calculate the relative daily change in the CDS spread of each of the government bonds. Therefore, the following formula applies:

$$r_{CDS,c,t} = \frac{CDS_{c,t}}{CDS_{c,t_{previous}}} - 1 \quad (3)$$

To assess sensitivities to stock markets, we collected daily data on the index prices of the Euro Stoxx 50 from Refinitiv. The index comprises the stock prices of 50 large corporations with liquid shares from Euro area countries and is widely recognized as a reliable indicator of the overall growth of the European economy, as documented by Brechmann and Czado (2013). In an empirical model, the market index returns $r_{m,t}$ account for macroeconomic shocks that affect all insurers simultaneously (cf. Hartley et al. (2017)). They are defined as:

$$r_{m,t} = \frac{Euro\ Stoxx\ 50_t}{Euro\ Stoxx\ 50_{t_{previous}}} - 1 \quad (4)$$

The summary statistics of the variables used to measure interest rate risk, credit risk, and the stock market sensitivities over the time period from 2006 to 2019 are presented in Table 1. Sovereign CDS spreads are reported for each country. In absolute terms, the 5-year CDS spreads range from 0.0108% (observed for Finnish government bonds in June 2007) to 232%

(observed for Greek government bonds in January 2013). In a robustness test, we use national stock indices instead of the Euro Stoxx 50 to measure insurers' sensitivities to stock markets. The summary statistics for the national stock indices are shown in Table A2 in Appendix I.

| | N | Mean | Median | SD | p1 | p5 | p95 | p99 |
|---|---|---|---|---|---|---|---|---|
| **Insurer characteristics (insurer-day level in ppt)** | | | | | | | | |
| $\mathrm{TRI}_{i,t}$ (stock price level) | 157,491 | 4,828 | 495 | 15,178 | -17.5 | -44.2 | 18,286 | 99,350 |
| $\mathrm{r}_{i,t}$ (stock return) | 157,434 | 0.04 | 0.00 | 2.30 | -6.24 | -3.14 | 3.23 | 6.61 |
| **Interest rate risk variables (day level in ppt)** | | | | | | | | |
| $\mathrm{y10}_t$ (10-year interest level) | 3,519 | 2.09 | 2.00 | 1.58 | -0.52 | -0.12 | 4.34 | 4.59 |
| $\mathrm{r}_{y10,t}$ (10-year hpr) | 3,519 | 0.011 | 0.018 | 0.37 | -0.97 | -0.60 | 0.59 | 0.91 |
| **Credit risk variables (country-day level in ppt)** | | | | | | | | |
| $\mathrm{CDS}_{c,t}$ (CDS level, all countr.) | 52,783 | 2.57 | 0.36 | 5.03 | 0.014 | 0.021 | 4.46 | 23.32 |
| $\mathrm{r}_{CDS,c,t}$ (CDS return, all c.) | 52,781 | 0.13 | 0.00 | 3.98 | -9.57 | -4.92 | 5.67 | 12.84 |
| $\mathrm{CDS}_{Austria,t}$ (CDS level) | 3,519 | 0.45 | 0.26 | 0.50 | 0.016 | 0.018 | 1.64 | 2.10 |
| $\mathrm{CDS}_{Belgium,t}$ (CDS level) | 3,519 | 0.62 | 0.38 | 0.72 | 0.021 | 0.024 | 2.40 | 3.09 |
| $\mathrm{CDS}_{Denmark,t}$ (CDS level) | 3,519 | 0.30 | 0.20 | 0.33 | 0.013 | 0.021 | 1.17 | 1.36 |
| $\mathrm{CDS}_{Finland,t}$ (CDS level) | 3,519 | 0.24 | 0.22 | 0.19 | 0.012 | 0.015 | 0.68 | 0.85 |
| $\mathrm{CDS}_{France,t}$ (CDS level) | 3,519 | 0.47 | 0.31 | 0.49 | 0.015 | 0.017 | 1.73 | 2.14 |
| $\mathrm{CDS}_{Germany,t}$ (CDS level) | 3,519 | 0.25 | 0.18 | 0.24 | 0.015 | 0.017 | 0.84 | 1.02 |
| $\mathrm{CDS}_{Greece,t}$ (CDS level) | 3,519 | 28.97 | 4.85 | 65.94 | 0.053 | 0.079 | 231.89 | 231.89 |
| $\mathrm{CDS}_{Ireland,t}$ (CDS level) | 3,519 | 1.59 | 0.54 | 2.22 | 0.018 | 0.023 | 7.00 | 8.56 |
| $\mathrm{CDS}_{Italy,t}$ (CDS level) | 3,519 | 1.43 | 1.18 | 1.17 | 0.061 | 0.086 | 4.37 | 5.35 |
| $\mathrm{CDS}_{Netherlands,t}$ (CDS level) | 3,519 | 0.32 | 0.24 | 0.29 | 0.012 | 0.018 | 1.02 | 1.24 |
| $\mathrm{CDS}_{Norway,t}$ (CDS level) | 3,519 | 0.16 | 0.14 | 0.10 | 0.013 | 0.016 | 0.39 | 0.50 |
| $\mathrm{CDS}_{Poland,t}$ (CDS level) | 3,518 | 0.95 | 0.73 | 0.68 | 0.085 | 0.135 | 2.45 | 3.10 |
| $\mathrm{CDS}_{Slovenia,t}$ (CDS level) | 3,518 | 1.20 | 0.82 | 1.08 | 0.036 | 0.044 | 3.73 | 4.31 |
| $\mathrm{CDS}_{Spain,t}$ (CDS level) | 3,519 | 1.25 | 0.76 | 1.29 | 0.026 | 0.030 | 3.97 | 5.55 |
| $\mathrm{CDS}_{UK,t}$ (CDS level) | 3,519 | 0.37 | 0.27 | 0.29 | 0.013 | 0.016 | 0.91 | 1.27 |
| **Equity risk variables (day level in ppt)** | | | | | | | | |
| Euro Stoxx $50_t$ (market index) | 3,519 | 3,165 | 3,141 | 559 | 2,092 | 2,269 | 4,242 | 4,470 |
| $\mathrm{r}_{m,t}$ (market return) | 3,519 | 0.009 | 0.028 | 1.38 | -3.87 | -2.14 | 2.10 | 3.47 |

Note: The stock price and stock return are at the insurer-day level and are obtained from Refinitiv. Insurers' interest rate sensitivities are measured by the hpr of 10-year interest rates collected from the ECB at the day level. Credit risk variables are at the country-day level and retrieved from IHS Markit. To estimate insurers' sensitivities to stock markets, we use the daily return of the Euro Stoxx 50 index retrieved from Refinitiv. While returns are used for the regression analyses, the table also shows the levels of the corresponding variables for information purposes. The sample starts on 20 March 2006 and ends on 30 December 2019. It includes 49 European insurers.

*Table 1: Descriptive statistics for the first stage of the empirical analysis*

The Pearson correlation matrix of the independent variables is shown in Table 2 below. Notably, the correlation between the interest rate hpr and the CDS spread returns is relatively low (0.18). The augmented Dickey-Fuller test and the variance inflation factor suggest that the independent variables are stationary and that there is no multicollinearity.

| **Correlation coefficients** | $r_{y10,t}$ | $r_{CDS,c,t}$ | $r_{m,t}$ |
|---|---|---|---|
| $r_{y10,t}$ | 1 | | |
| $r_{CDS,c,t}$ | 0.18 | 1 | |
| $r_{m,t}$ | −0.31 | −0.33 | 1 |

*Table 2: Correlation matrix of independent variables*

## 2.3 Regression model

In the first stage of our regression analyses, we consider the effects of changes in interest rates, CDS spreads, and stock market indices on insurers' performance over the period from 2006 to 2019.[6] In line with previous studies that have performed firm-level regressions with stock returns to obtain individual betas (cf. Berends et al. (2013), Brewer et al. (2007), Campbell et al. (2001), and Da et al. (2012)), we analyze market risk sensitivities at the insurer level using time-series data. This approach allows us to investigate the heterogeneity in market risk exposures across insurers, as highlighted by Berends et al. (2013) and Möhlmann (2021). Following the approach of Düll et al. (2017), we apply logarithmic transformations to all variables, which allows us to interpret the beta coefficients as elasticities.

To determine insurers' market risk sensitivities, we use rolling time windows, building on the approach of Hartley et al. (2017). This allows us to account for changes in insurers' risk profiles, as Brewer et al. (2007) show that sensitivities vary over time. The time windows cover a time frame of 10 years each, resulting in five periods $p$: 2006 to 2015, 2007 to 2016, 2008 to 2017, 2009 to 2018, and 2010 to 2019.[7] The motivation for choosing revolving 10-year time frames is that the decision of whether to use an LTG measure or an internal model under Solvency II should be based on an insurer's long-term risk profile, which we measure through sensitivities to stock performance over several years. These include times of crises such as the global financial crisis (2007-2009) and the European sovereign debt crisis (2010-2013), when the market risk sensitivities of individual companies become more visible.

For each period $p$, we run an OLS regression for each of the 49 insurers $i$ in the sample, given that stock data are available. We obtain insurer-specific and period-specific measures of interest rate risk, credit risk and stock market sensitivities. In this way, the approach provides individual risk profiles of insurance companies based on stock market reactions. The linear regressions for each insurer $i$ in the sample and for each period $p$ are based on the following model:

$$\begin{aligned} ln(r_{i,t}+1) = \alpha + \beta_{y10,i,p} ln(r_{y10,t}+1) + \ \beta_{CDS,i,p} ln(r_{CDS,c(i),t}+1) \\ + \beta_{m,i,p} ln(r_{m,t}+1) + \varepsilon_{i,p,t} \end{aligned} \tag{5}$$

[6] Considering these three market risk factors in a joint model mitigates the risk of omitted variable bias that could arise if the market risk factors were analyzed separately. Similarly, in line with the requirements of Solvency II, European insurers are obliged to consider all market risks and their interdependencies, as set out in Article 164 of the European Commission (2015).

[7] Our empirical results are robust to using shorter time windows, as shown in Table A5 in Appendix IV.

In Equation (5), $c(i)$ reflects the country in which insurer $i$ is domiciled. An insurer's daily stock return, denoted by $r_t$ for each day $t$, serves as the dependent variable. The first independent variable is $r_{y10,t}$, which indicates the 1-day hpr of a 10-year AAA-rated zero-coupon bond. The second independent variable, $r_{CDS,c(i),t}$, measures changes in CDS spreads on domestic sovereign debt, based on an insurer's country of headquarters. The last independent variable, $r_{m,t}$, reflects daily changes in the Euro Stoxx 50 index. The residual term in the regression of insurer $i$ and period $p$ is denoted by $\varepsilon_{i,p,t}$. We stored the estimated beta coefficients $\beta_{y10,i,p}$, $\beta_{CDS,i,p}$ and $\beta_{m,i,p}$ for each insurer $i$ and period $p$ from all 232 regressions as inputs for the second stage of our empirical analysis in Section 3. The betas indicate the direction of the relationship between each market risk driver and each insurer's stock price, as well as the magnitude of their influences during a given time window.

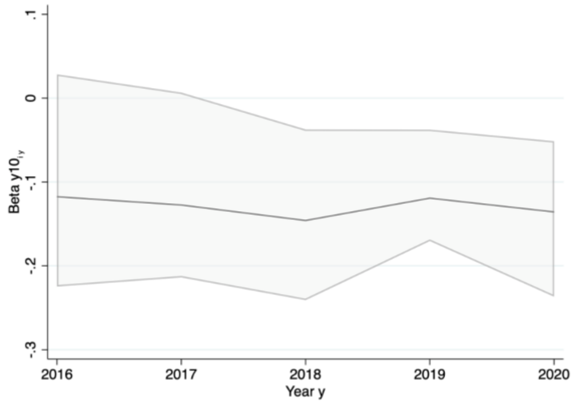
## 2.4 Resulting sensitivities

Our findings on insurers' sensitivities to market risk drivers are broadly consistent with previous empirical studies. With respect to interest rate risk, our results show that most insurers benefit from higher 10-year interest rates (cf. Hartley et al. (2017), Grochola et al. (2023)). This can be seen in the fact that 78% of the coefficients $\beta_{y10,i,p}$ are negative, meaning that the insurers suffer from a higher hpr, as measured by $r_{y10,t}$.[8] For a median insurer, a 1% decrease in the 1-day hpr of 10-year rates causes a 0.128% decrease in its stock return, holding the other regressors constant. Of the 232 estimated interest rate sensitivities, 41% are statistically significant at the 10% level. The evolution of the distribution of the estimated interest rate betas over time is shown in Figure 1a), where the median and the 25th and 75th percentiles (upper and lower bounds of the shaded area) are plotted. For each year $y$ (2016 to 2020), we show the betas estimated on the basis of the ten years preceding that year. For instance, the insurer-level beta coefficients for the year 2020 depend on the sensitivities in the period from 2010 to 2019. While the median interest rate beta is relatively constant over time, the 50% interval of all estimates becomes narrower, as the time period of the global financial crisis is not (or not fully) covered when estimating the regression coefficients for later years.

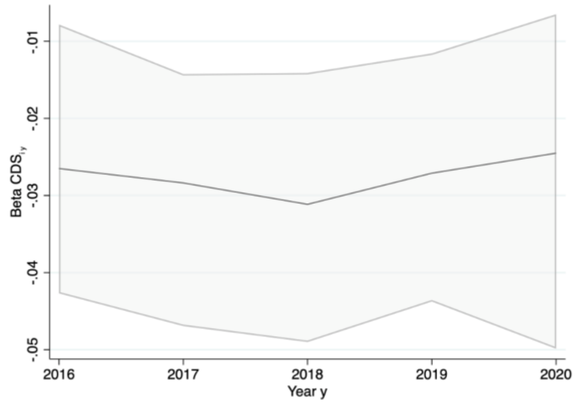
Regarding credit risk sensitivities, European insurers benefit from a lower probability of default on domestic sovereign debt in line with Düll et al. (2017) and Grochola et al. (2023). More clearly than for interest rates, the estimated coefficients $\beta_{CDS,i,p}$ are mostly negative (91% of all

[8] According to our estimates, the insurer suffering the most from falling interest rates in our sample is Storebrand ASA, the largest life insurer in Norway. In contrast, the insurer that benefits most from falling interest rates is Pozavarovalnica Sava dd, a relatively small non-life insurer from Slovenia.

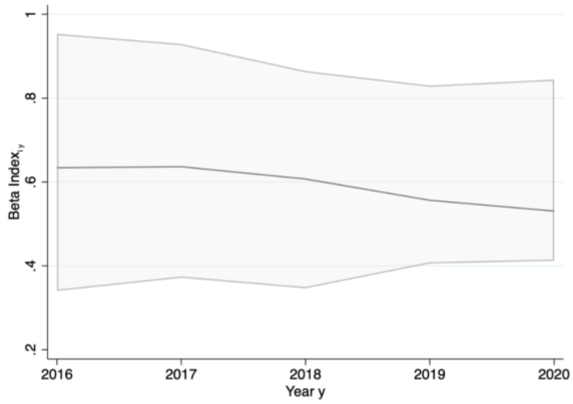
betas) and significant at the 10% level (67% of all betas).[9] The median implies that, ceteris paribus, a 1% increase in domestic CDS spreads reduces an insurer's stock return by 0.028%. The effect of a 1% change is, thus, relatively smaller compared to 10-year interest rates. As shown in Figure 1b), the 50% interval of all betas is fairly constant over time.




(a) Interest rate risk




(b) Credit risk




(c) Stock market sensitivities

Note: The regression coefficients (y-axis) are estimated based on the insurer-level regression analyses formulated in Equation (5). The sensitivities of each year depend on the influence of the market risk drivers on the stock performance of insurers over the ten years preceding year $y$ (x-axis). The top (bottom) line reflects the 75th (25th) percentile of the distribution in a given year. The middle line represents the median. The gray area corresponds to the 50% interval of the beta estimates.

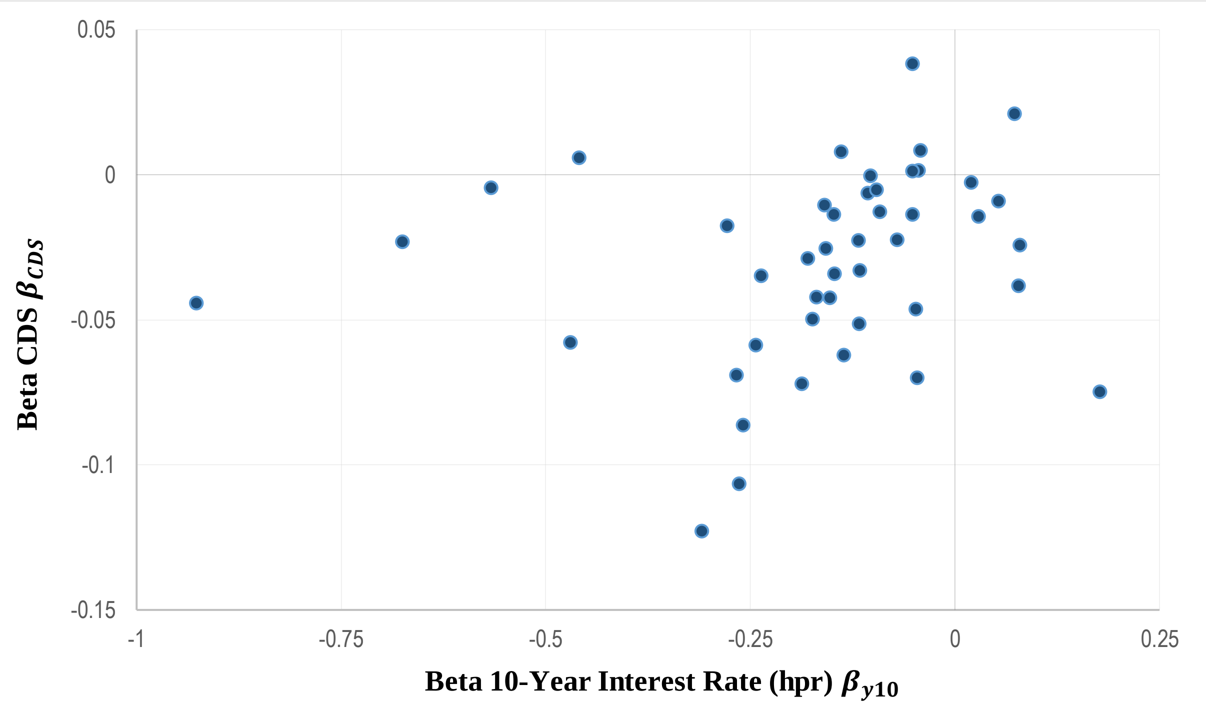
*Figure 1: Estimated market risk sensitivities (betas)*

Insurers' sensitivities to stock market performance are the most important drivers of insurers' stock returns. The relationship is positive for all insurers in the sample and the coefficients $\beta_{m,i,p}$ are significant at the 10% level for 97.8% of the estimates. Insurers' stock returns are thus positively related to the Euro Stoxx 50 index, even after controlling for changes in interest rates and CDS spread.[10] Figure 1c) shows that both the 75th percentile and the median of the

[9] Belgian insurers Ageas SA and KBC Groep NV show the greatest credit risk sensitivities in our sample, with beta coefficients as low as -0.16. We do not find any insurers that benefit significantly from rising CDS spreads.
[10] We observe the highest stock market sensitivity coefficients of up to 1.49 for two large insurance groups: Aegon NV from the Netherlands and AXA SA from France.

beta coefficients fall slightly in later years, indicating a decreasing dependence of insurers' performance on stock markets or overall economic growth in Europe.

The estimated insurer-level sensitivities to interest rate risk and credit risk are shown in Figure 2 for the period from 2010 to 2019. A blue dot in the lower left-hand corner of the figure would represent an insurer that suffers greatly from both falling interest rates and rising CDS spreads. The distribution illustrates the heterogeneity of European insurers' market risk profiles, which can be related to several factors such as the share of life business, the riskiness of investments, the width of duration gaps or the use of guarantees for life insurance policies. Notably, of the 10 insurers for which we estimate the highest interest rate risk (credit risk), nine insurers (eight insurers) use at least one LTG measure. In particular, we observe that many insurers with higher interest rate risk use the volatility adjustment and that it has a relatively larger impact on their reported solvency ratio. Similarly, insurers with higher credit risk tend to use the matching adjustment, which can substantially increase the solvency ratio. Anecdotal evidence for five insurers with large market risk sensitivities is shown in Figure A1 in Appendix II.




Note: Each dot reflects an insurer's estimated regression coefficients $\beta_{y10,i,p}$ and $\beta_{CDS,i,p}$ from Equation (5) over the period from 2010 to 2019. An insurer on the lower left would substantially suffer from falling 10-year interest rates and rising CDS spreads of domestic sovereign debt.

*Figure 2: Insurer-specific estimates for sensitivities to interest rate and CDS changes*

The estimated beta coefficients measuring the sensitivities to interest rate risk $\beta_{y10,i,p}$ and credit risk $\beta_{CDS,i,p}$ are almost perfectly uncorrelated, as shown in Table 3. The correlation coefficients are negative and larger between the stock market sensitivity $\beta_{m,i,p}$ and the other two sensitivity measures. This suggests that insurers that suffer more from falling interest rates or rising CDS spreads also tend to suffer more from falling stock market indices.

| **Correlation coefficients** | $\beta_{y10,i,p}$ | $\beta_{CDS,i,p}$ | $\beta_{m,i,p}$ |
|---|---|---|---|
| $\beta_{y10,i,p}$ | 1 | | |
| $\beta_{CDS,i,p}$ | 0.01 | 1 | |
| $\beta_{m,i,p}$ | −0.40 | −0.37 | 1 |

*Table 3: Correlation matrix of market risk estimates (betas)*

All estimated insurer-level betas used in the second stage of the regression analyses described in Section 3, are presented in Table A3 in Appendix II.[11] Summary statistics are provided in Table 4. In the remainder of this paper, we will refer to the beta variables as sensitivities to each market risk (interest rate risk, sovereign credit risk, and stock market movements).

# 3 Determinants of discretionary decisions under Solvency II

## 3.1 Data

In the second stage of the empirical analysis, we investigate insurers' discretionary decisions under Solvency II. For this purpose, we use data published in the SFCRs of the years 2016 to 2020 for all 49 stock insurers in the sample. We only use Solvency II publications on the group level. Quantitative regulatory data for 164 out of 233 insurer-year observations was gathered from the data provider SNL and is based on Quantitative Reporting Templates (QRTs). We have substantially double-checked the SNL data with hand-collected data from original SFCR publications and have corrected seven insurer-year observations. For the remaining 69 insurer-year observations, the quantitative data was hand-collected from QRTs.

To the best of our knowledge no provider yet offers data about the composition of internal models as reported in the SFCRs. Therefore, we have hand-collected information from the SFCRs about important aspects of the design of internal models. This includes information such as whether certain risk modules are modeled internally and whether the risks related to investments in EU government bonds are taken into consideration. Even though the data is partly provided as textual information and in languages other than English, we were able to collect it for all 233 insurer-year combinations.[12]

[11] The missing values ("NA") in Table A3 can be explained either by missing stock price data or by insurer-year observations that we removed due to missing SFCR data in the second stage of the regression analyses.
[12] While the majority of SFCRs and QRTs are in English, we also collected data from 9 insurers (33 insurer-year combinations) that did not publish their reports in English. 15 of these combinations are in German, 7 in Spanish, 7 in Danish, 2 in French and 2 in Norwegian. Details of the coding are given further below for each variable.

In terms of the QRT data, our focus is on information which is based on the firm managements' discretionary decisions. This is mainly reflected by the use of LTG measures, i.e., the matching and volatility adjustment as well as the transitionals on technical provisions and interest rates.[13] These measures were introduced in 2014 as an amendment to the Solvency II framework directive. The matching (77b and c) and the volatility adjustment (77d) are subordinated to Article 77 of the European Commission (2009) dealing with the calculation of technical provisions. The two other LTG measures are elaborated upon in Articles 308c and 308d of the European Commission (2009), dealing with transitional provisions for insurers and reinsurers. The transitionals can only be used temporarily and allow insurers to gradually adjust to the regulatory changes in the calculation of capital reserves and risk-free interest rate assumptions for contracts concluded before 2016 until the year 2032 (cf. EIOPA (2016b)).

All four LTG measures influence – and typically improve – the reported solvency of insurance companies. Solvency II regulation prescribes capital buffers in the form of solvency capital requirements (SCR) to cover for the potential negative consequences of an insurer's true risk profile. The SCR is intended to ensure that the company's ruin probability over a one-year time horizon does not exceed 0.5%. The central outcome of Pillar I, which focuses on quantitative requirements for insurers, is the solvency ratio which equals an insurer's eligible own funds divided by its SCR:

$$Solvency\ Ratio_{i,y} = \frac{Eligible\ Own\ Funds_{i,y}}{SCR_{i,y}} \tag{6}$$

Overall, the insurers in our sample had an SCR of €253 billion in 2020. This corresponds to a market share of 59% based on the aggregate SCR for all insurance groups reported by EIOPA (2020).[14] Eligible own funds amounted to €531 billion in 2020 (market share of 59%), resulting in an average reported solvency ratio of 210% in our sample.

The solvency ratio is regularly used as a stand-alone measure of an insurer's solvency position (cf. Crean and Foroughi (2017) and Mukhtarov et al. (2022)). Both the numerator and the denominator of the solvency ratio can be affected by LTG measures. The impact of each measure on an insurer's own funds and the SCR is typically presented in the QRT form

[13] The composition of the optional measures described as "LTG measures" is in line with EIOPA (2020). Other measures do not reflect optional decisions (e.g., the symmetric adjustment to the equity risk change) or are hardly used (e.g., the duration-based equity risk submodule is used by only one insurer in France, cf. EIOPA (2020)).
[14] Note that EIOPA's LTG report from 2020 excludes UK insurers for the first time, even though Solvency II regulation was still binding under UK national law and reforms were not announced until 2022 (cf. Chaplin et al. (2022)). We subtract the SCR for UK insurers in our sample before calculating the market share. The remaining 41% of the market share is associated with European insurance groups that are not listed on the stock exchange.

S.22.01.22.[15] All SFCRs and corresponding QRTs are publicly available and typically accessible through an insurer's investor relations department. Table A4 in Appendix III presents the collected quantitative data from the SFCRs for the years 2016 to 2020 of all 49 insurers in the sample and the chosen model for calculating the SCR. Notably, insurers can choose to use more than one LTG measure in a year. The table shows a large heterogeneity in the use of LTGs across European insurers, with particularly large insurers typically using at least one.

In our sample, the number of insurer-year observations with an applied LTG varies between 6 for the transitional for interest rates, 30 for the matching adjustment, 77 for the transitional for technical provisions, and 149 for the volatility adjustment. In total, we find 262 applications for the 233 insurer-year observations. An average insurer thus uses 1.12 LTGs per year. In 259 of the 262 applications, the LTG measure increases the reported solvency ratio,[16] and for all 233 insurer-year observations, the sum of all measures has a positive overall effect. Therefore, the use of LTGs reflects latitude in the implementation of Solvency II and contains potentially relevant information for policyholders, investors, and other stakeholders. To this end, we examine factors that drive these discretionary decisions and their impact on the solvency ratio.

As we systematically analyze SFCRs and the corresponding QRTs, we calculate the impact of the use of the LTG measures on the solvency ratio from Equation (6). In our sample, the reported solvency ratio would have been on average up to 29ppt lower without the use of these measures.[17] EIOPA (2016b, 2020) initially presents even larger impacts of LTGs of 60ppt in 2016, followed by only 28ppt in 2020 due to a falling influence of transitionals on the solvency ratio and due to insurers adapting to the new regulation standards. For up to 7.3% of our observations, insurers would have to report solvency ratios below 100%,[18] which implies that their own funds are insufficient to meet regulatory requirements under the first pillar of Solvency II (cf. Article 100, European Commission (2009)). In this case, insurers are obligated to take corrective actions in line with the regulations of the national supervisory authority to restore compliance within six months (cf. EIOPA (2016b)). Potential actions include capital

[15] Few insurers use the more extensive QRT form S.22.01.21, which is binding for insurers on the solo entity level, to also report the influence of LTG measures on the group level. Insurance groups that do not use any LTG measure do not need to report the QRT form S.22.01.22. For these insurers, we collect data on eligible own funds and the SCR from the QRT form S.23.01.22.

[16] The three exceptional cases in which an LTG measure reduces the solvency ratio occur when insurers apply three LTG measures simultaneously over several years and one of the three measures has a temporary negative effect on the solvency ratio. In only one case is the effect greater than 1ppt.

[17] 29ppt is the difference between the average reported solvency ratio and the average ratio after subtracting the sum of the effects of all LTG measures. If only the largest LTG impact is subtracted, the difference is 23ppt.

[18] 7.3% represents the share of solvency ratios below 100% when the effects of all LTG measures are added up for a given insurer-year. The share is 6% when only excluding the LTG with the largest impact. We do not observe a case where an insurer does not comply with SCR according to its reported solvency ratio.

injections, recovery and restructuring plans, and sanctions.[19] Similarly to us, EIOPA (2017b, 2020) reports a share of insurers requiring LTG measures to meet the SCR of 11% in 2017 and 4% in 2020.

In our analyses, we aim to include the solvency ratio that insurers would experience without the use of LTGs. This is possible for 161 out of 233 insurer-year observations, when insurers do not simultaneously use at least one of the two adjustments (volatility and matching adjustment) and at least one of the two transitionals. However, if they do so, the "true" solvency ratio cannot be accurately calculated based on the QRTs, because they only report the impact per LTG, and the adjustments and transitionals influence each other. Therefore, the exact solvency ratio without all LTG measures cannot be determined for insurers using at least one of the adjustments or transitionals in the same year. Hence, we calculate the solvency ratio in the absence of each LTG measure $k$ for each insurer $i$ and each year $y$. If an insurer does not apply LTG $k$ in a given year, the impact of the LTG is zero.

$$Solvency\ pre\ LTG\ k_{i,y} = Solvency\ Ratio_{i,y} - Impact\ of\ LTG\ k_{i,y} \quad ,with\ k = \{VA, MA, TP\} \tag{7}$$

The overall descriptive statistics of the variables used in the second stage of our empirical analysis are presented in Table 4. This includes the Solvency II quantitative data mentioned in Equation (7) and binary variables reflecting the composition of internal models. As potential determinants of insurers' discretionary choices regarding LTG measures, we use the insurer level sensitivity coefficients (betas) estimated in the first stage (cf. Equation (5)) and two distinguishing firm characteristics: the share of insurance reserves stemming from life and health insurance business and the natural logarithm of the size (measured by total tangible assets). Without the firm characteristics, we have 232 total observations and our models including the firm characteristics rely on 225 observations.[20]

The four LTGs have different functions, frequencies of application and impacts on the solvency ratio. Figure 3 illustrates the use of LTG measures in the year 2020, where "TP" stands for transitional for technical provisions, "IR" for the interest rate transitional, "VA" for volatility

[19] For instance, the Cypriot non-life insurer Cosmos Insurance PCL reported a solvency ratio of 65.6% and had to initiate a recapitalization and restructuring plan to bolster its solvency position. The consequences are more severe if an insurer does not comply with the Minimum Capital Requirement (MCR) which usually accounts for 25% to 45% of SCR. The supervisor intervenes directly and withdraws the firm's business license if the MCR is not met again within a period of three months (cf. EIOPA (2016b)).

[20] The difference between the number of observations for beta coefficients and Solvency II quantitative data is due to the Dutch life insurer ASR Nederland, which was not listed on the stock exchange until 10 June 2016. Therefore, no regressions were run in the first stage for this insurer in 2016. In terms of firm characteristics, we have missing life insurance share data for KBC Groep NV from Belgium and Old Mutual PLC from the U.K.

adjustment, and "MA" for matching adjustment". The blue columns on the left show how many insurers in our sample use a particular LTG measure, and the gray columns on the right show the mean effect under the condition that the LTG is used.

| | N | Mean | Median | SD | p1 | p5 | p95 | p99 |
|---|---|---|---|---|---|---|---|---|
| **Beta coefficients from first stage** | | | | | | | | |
| Sensitivity $y10_{i,y}$ (interest rate) | 232 | -0.14 | -0.13 | 0.18 | -0.74 | -0.46 | 0.11 | 0.23 |
| Sensitivity $CDS_{i,y}$ (credit risk) | 232 | -0.03 | -0.03 | 0.03 | -0.15 | -0.09 | 0.01 | 0.03 |
| Sensitivity $Index_{i,y}$ (stock market) | 232 | 0.65 | 0.62 | 0.36 | 0.06 | 0.10 | 1.36 | 1.48 |
| **Solvency II quantitative data (in ppt)** | | | | | | | | |
| VA $Impact_{i,y}$ (abs. effect on Solvency) | 233 | 0.11 | 0.02 | 0.20 | 0.00 | 0.00 | 0.49 | 0.98 |
| MA $Impact_{i,y}$ (abs. effect on Solvency) | 233 | 0.07 | 0.00 | 0.26 | 0.00 | 0.00 | 0.50 | 1.57 |
| TP $Impact_{i,y}$ (abs. effect on Solvency) | 233 | 0.11 | 0.00 | 0.21 | 0.00 | 0.00 | 0.58 | 0.77 |
| Solvency pre $VA_{i,y}$ | 233 | 1.92 | 1.86 | 0.45 | 1.12 | 1.26 | 2.81 | 3.16 |
| Solvency pre $MA_{i,y}$ | 233 | 1.96 | 1.98 | 0.54 | 0.25 | 1.00 | 2.85 | 3.18 |
| Solvency pre $TP_{i,y}$ | 233 | 1.92 | 1.93 | 0.42 | 0.99 | 1.23 | 2.57 | 3.16 |
| Solvency pre $LTG1_{i,y}$ | 233 | 1.80 | 1.79 | 0.49 | 0.25 | 0.98 | 2.49 | 3.11 |
| **Solvency II modeling (binary)** | | | | | | | | |
| Internal $Model_{i,y}$ | 233 | 0.51 | 1.00 | 0.50 | 0.00 | 0.00 | 1.00 | 1.00 |
| Internal Market $Risk_{i,y}$ | 233 | 0.41 | 0.00 | 0.49 | 0.00 | 0.00 | 1.00 | 1.00 |
| Internal Interest Rate $Risk_{i,y}$ | 233 | 0.36 | 0.00 | 0.48 | 0.00 | 0.00 | 1.00 | 1.00 |
| Internal Spread $Risk_{i,y}$ | 233 | 0.39 | 0.00 | 0.49 | 0.00 | 0.00 | 1.00 | 1.00 |
| Internal Default $Risk_{i,y}$ | 233 | 0.32 | 0.00 | 0.47 | 0.00 | 0.00 | 1.00 | 1.00 |
| EU Gov Bond Spread $Risk_{i,y}$ | 233 | 0.19 | 0.00 | 0.40 | 0.00 | 0.00 | 1.00 | 1.00 |
| EU Gov Bond Default $Risk_{i,y}$ | 233 | 0.09 | 0.00 | 0.28 | 0.00 | 0.00 | 1.00 | 1.00 |
| **Firm characteristics** | | | | | | | | |
| Life $Share_{i,y}$ (in ppt) | 226 | 0.42 | 0.45 | 0.29 | 0.00 | 0.00 | 0.85 | 0.96 |
| $\ln(Size_{i,y})$ | 231 | 17.35 | 17.59 | 2.00 | 12.97 | 14.09 | 20.39 | 20.63 |

Note: The variables for the second stage of the regression analyses are all at the insurer-year level. The beta coefficients are collected from the firm stage, based on Equation (5). All Solvency II data (both quantitative and modeling data) are hand-collected from SFCRs. Other firm characteristics are obtained from SNL. The sample begins in 2016 and ends in 2020. It consists of 49 European insurers.

*Table 4: Descriptive statistics for the second stage of the empirical analysis*

To gradually adapt to the changes in the regulatory framework from Solvency I to Solvency II, insurers are allowed to use transitionals for technical provisions (1) and interest rates (2). The transitional for technical provisions enables insurers to smooth the capital impact over a 16-year period, during which the effect of the transitional declines linearly. Similarly, the transitional for interest rates spreads the impact of the change in interest rate calculation standards over the same period (cf. EIOPA (2018)). The former was applied by 35.6% of the stock insurers in the sample in 2020, considerably increasing their solvency ratios by 27.4ppt on average (cf. Figure 3). However, the effect diminishes over time, as the transitional effect was 35.3ppt in 2016. In contrast, the transitional for interest rates is not widely used, as only one to two insurers in our sample apply it each year. Therefore, we do not run regressions to analyze the determinants of the interest rate transitional. Instead, for the transitional on technical provisions, we expect it to be used mainly by insurers with an otherwise low solvency ratio.

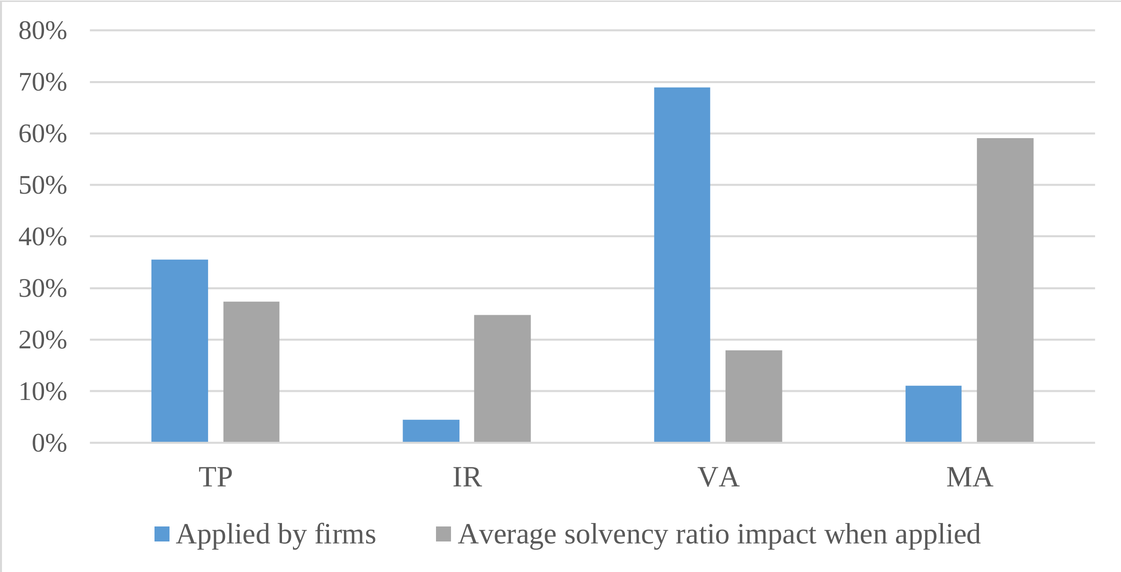



*Figure 3: Use of LTG measures in 2020*

In addition, we expect the impact of the volatility (3) and matching (4) adjustments on the solvency ratio to be related to insurers' market risk sensitivities. As the volatility adjustment mitigates the effect of short-term fluctuations in financial markets, it may be particularly relevant for insurers with wide duration gaps and thus higher interest rate risk. Notably, this LTG was used by as many as 68.9% of insurers in our sample in 2020 (cf. Figure 3) and is thus becoming more popular over time (50.9% in 2016). The average effect on the solvency ratio is relatively constant. For the matching adjustment, its use is linked to regulatory requirements, including appropriate duration matching and the declaration to hold assets until maturity (cf. EIOPA (2018)). Therefore, it was only applied by 11.1% of stock listed insurers in 2020. Typically, the matching adjustment lowers the capital requirement for spread risk and thus improves the solvency ratio. We expect this measure to be applied mainly by insurers with riskier fixed-income investments and thus higher credit risk sensitivities. Of the four LTGs, the matching adjustment has the largest average impact on the solvency ratio at 59.1ppt. This effect is notable given that Grochola et al. (2023) show that interest rate risk is five times more relevant than sovereign credit (or spread) risk for European insurers. Both the share and the impact of the matching adjustment are relatively constant over the sample period. Notably, there is heterogeneity in the impact of LTGs, as we observe extreme cases in which the volatility adjustment improves a solvency ratio from 102% to 230% and the matching adjustment from only 25% to 189%.[21]

[21] Cf. Table A4 in Appendix III, with NN Group NV and Legal & General Group PLC, both in 2018.

In addition to the LTG measures, there are several other discretionary decisions in the calculation of the SCR that we collect from the SFCRs. In particular, we examine whether insurers use an internal model or the standard formula. The standard formula determines the SCR in a multilevel approach, the structure of which is shown in a simplified form in Figure 4 that illustrates the bottom-up approach of Solvency II. At the lowest level, known as the submodules, the SCR is determined, for example, for interest rate risk and spread risk. These submodules are aggregated to the module level. Interest rate risk and (credit) spread risk are part of the market risk module, which is typically the largest risk component for calculating the SCR, accounting for 49% of the total undiversified SCR in our sample.[22] This corresponds to €189 billion. Another module reflects the SCR for counterparty default risk, which accounts for 6.4% of undiversified SCR (or 9.1% of total SCR). SCR covers several other types of risks, including insurance risks (health, life, non-life) and operational risks.

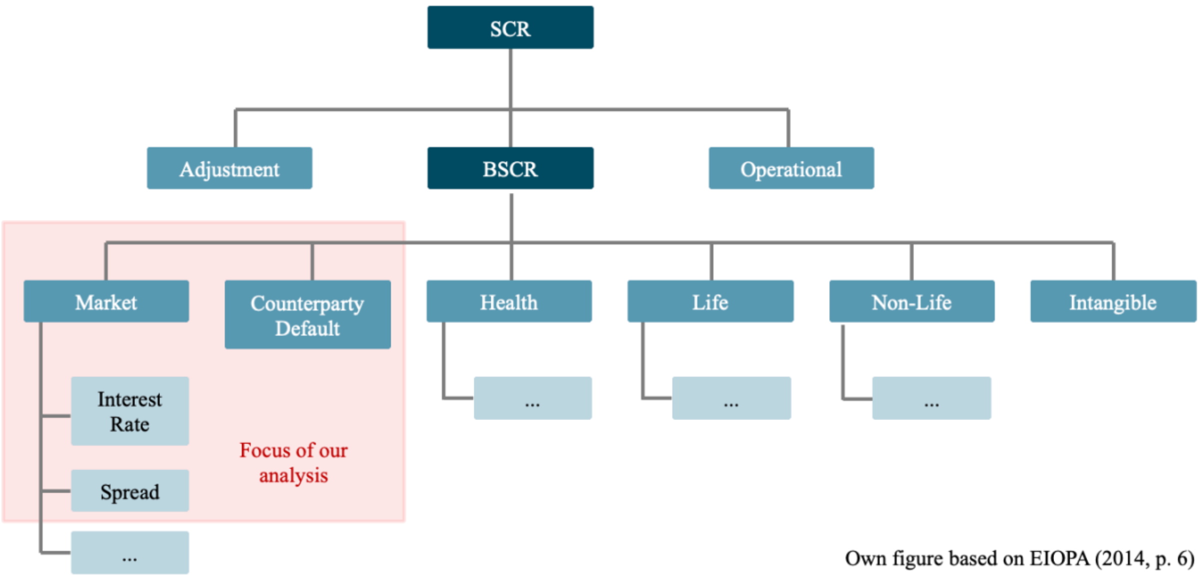



*Figure 4: Structure for SCR calculation under the standard formula*[23]

Insurers can replace the complete SCR calculation for all group entities with their own "full" internal models. These are meant to better fit the insurers' risk profiles and are subject to regulatory approval. Full internal models can have a different structure for calculating SCR than the standard formula shown in Figure 4. Alternatively, insurers can model only selected

[22] The total SCR is typically lower than the undiversified SCR due to diversification effects between risk categories and due to adjustments including loss absorbing instruments and deferred taxes (cf. BaFin (2020)). Relative to the total SCR, the market risk model accounts for 72% of the capital requirements. The data is collected from the QRT forms starting with "S.25" (the remaining digits depend on the chosen SCR calculation model).

[23] Note that Figure 4 shows all existing SCR risk modules, but only 2 out of 27 submodules. For an overview of the entire structure, see EIOPA (2014, p. 6). In our analysis, we focus on selected SCR modules and submodules for which we assume that insurers have an incentive to model them internally or that discretionary choices are influenced by the beta sensitivities obtained from the first stage of regression analyses in Equation (5). BSCR stands for "Basic SCR" and includes diversification effects between the risk modules in the row below.

(sub)modules internally. If at least one subsidiary of an insurance group retains a (sub)module of the standard formula, it is referred to as a "partial" internal model.

We have hand-collected the information on the SCR calculation from Section E.4 of the SFCRs, entitled "Differences between the standard formula and any internal model used". Overall, we find that insurers use a full or partial internal model for 51% of the insurer-year observations (cf. Table 4). Only a few insurers (9.4% of observations) in our sample use full internal models. A much larger proportion of insurers (41.6% of observations) use partial internal models, which implies that most insurers choose to use the standard formula approach for at least one SCR module or submodule. For these firms, it is particularly interesting to observe which modules they calculate internally and to investigate potential drivers of these decisions. For this purpose, we construct several binary variables for the SCR (sub)modules (cf. Table 4). For example, $Internal\ Market\ Risk_{i,y} = 1$ if an insurer $i$ in a given year $y$ uses an internal model for the SCR market risk module (meaning that at least one submodule is modeled internally), and zero otherwise. Figure 5 shows the proportion of (sub)modules modeled internally for all insurers using internal models (either partially or fully) in 2020. Accordingly, 76% of insurers with internal models have modeled the market risk module internally, while the share for the counterparty default risk module is only 56%.

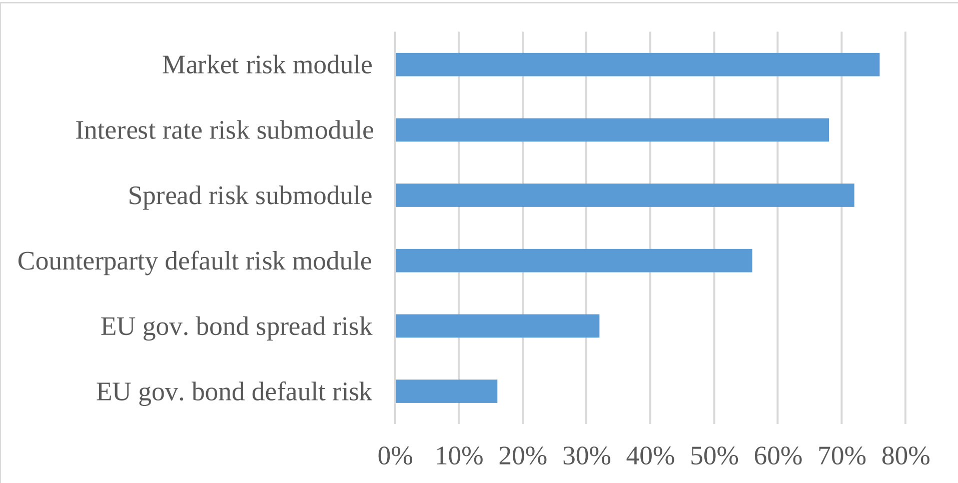
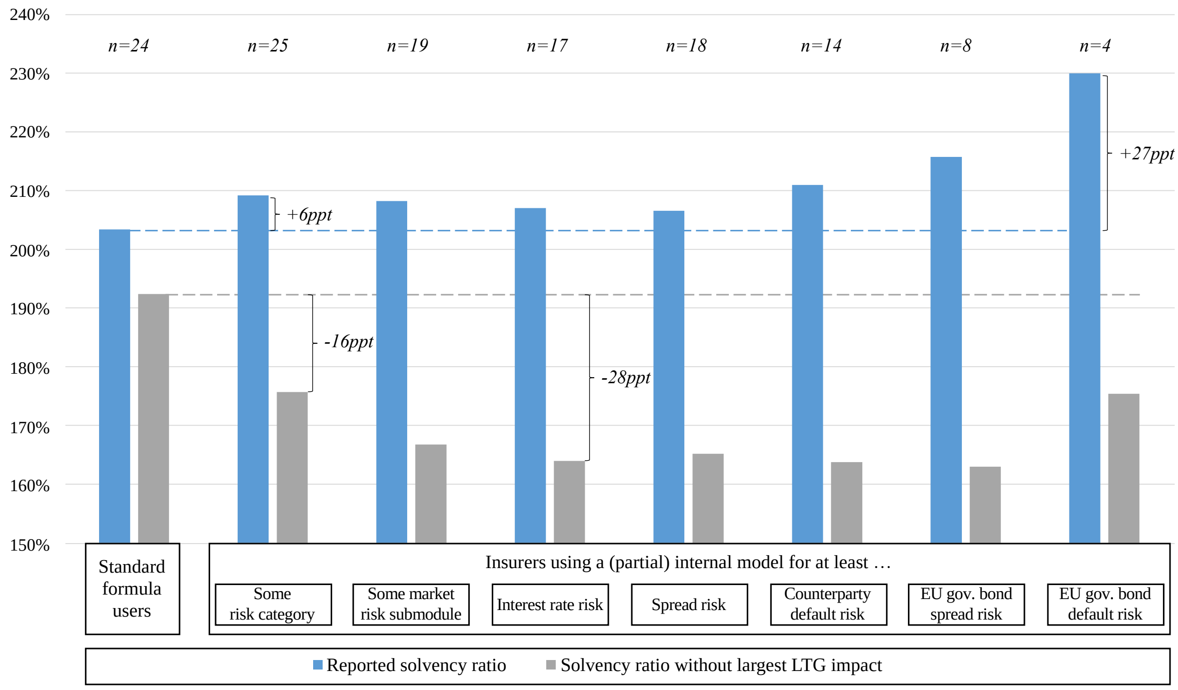



*Figure 5: Portion of insurers using an internal model per model component in 2020*

Moreover, we examine whether insurers using internal models consider the spread and default risk of investments in government bonds issued by European Union (EU) countries when calculating their SCR. According to Article 180 (2) of the European Commission (2015), insurers are not required to take into account the sovereign credit risk stemming from these investments under Solvency II. While this provision provides an incentive to invest in EU government bonds, it has been criticized for neglecting a true market risk, even though Solvency II aims for a market-consistent valuation of assets and liabilities (cf. Wilson (2013), Thibeault and Wambeke (2014), Düll et al. (2017)). For EU sovereign spread risk (default risk), we find that insurers voluntarily include this type of risk in their SCR calculation for 19% (9%) of insurer-year observations (cf. Table 4). Among all insurers using internal models in 2020, only a small proportion of insurers explicitly state in their SFCRs that they take these risks into account (32% and 16% respectively, cf. Figure 5). Typically, these are large insurers that model most SCR risk modules internally.




Note: The reported solvency ratio (blue) and the solvency ratio excluding the largest LTG impact (gray) are shown for different groups of insurers, namely standard formula users, insurers using a (partial) internal model for at least some risk category, and insurers using a (partial) internal model including a specific risk category.

*Figure 6: Solvency ratios based on internal model composition*

Notably, insurance groups that model risk internally tend to have higher reported solvency ratios than insurers that use the standard formula (cf. blue columns in Figure 6). Overall, insurers that calculate their SCR using a partial or full internal model report a solvency ratio that is 6ppt higher in 2020. For each (sub)module for which we collected data, we find that insurers that model them internally have higher average reported solvency ratios than insurers that use the standard formula to calculate SCR.[24] However, if we subtract the influence of the LTG measure that has the largest impact on the solvency ratio, we find that the solvency level

[24] For each (sub)module, we also find that insurers that model it internally report, on average, higher solvency ratios than insurers that use the standard formula to calculate that particular (sub)module. For instance, the ratio is higher when $Internal\ Market\ Risk_{i,y} = 1$ than when $Internal\ Market\ Risk_{i,y} = 0$.

of insurers using internal models is substantially lower (cf. gray columns in Figure 6). Overall, the difference is 16ppt, and for insurers modeling the interest rate risk submodule internally, the solvency ratio excluding the LTG with the largest impact is as much as 28ppt lower than for regular users of the standard formula. Similarly, the few insurers that include EU government bond default risk in their internal models have higher reported solvency ratios (27ppt), but are actually less solvent if the most influential LTG is excluded. These findings suggest that it is particularly important to pay attention to the impacts of LTG measures when insurers use internal models.

## 3.2 Empirical approach

In a first set of analyses to examine discretionary decisions in the implementation of Solvency II, we explain the use of LTG measures. To this end, we consider regression models with the impact of the LTG measure on the solvency ratio as the dependent variable ($VA\ impact_{i,y}$, $MA\ impact_{i,y}$ and $TP\ impact_{i,y}$). The regressors are the market risk sensitivities from the first stage of regression analyses and the solvency ratio calculated without each particular LTG from Equation (7). For instance, the coefficients for $Solvency\ pre\ VA_{i,y}$ can thus indicate whether the volatility adjustment is applied by insurers with otherwise lower solvency ratios. We also control for the size of the firms, measured by the natural logarithm of tangible assets, and the share of life insurance business, measured by the share of technical provisions from life and health insurance. The data for the two variables for size and life business are obtained from SNL. Since our sample consists of 49 insurance companies and we observe their solvency situation at three different points in time, we run panel regressions.

For each model, we use the Hausman test to determine whether fixed effects are present. In our models for the volatility and matching adjustment impact, the Hausman test suggests that fixed effects are not significant (p-values > 0.2). Therefore, we use random effects models, which are more efficient and control for autocorrelation. Notably, our results for these two models are robust to using fixed effects. Only in the model for the impact of the transitional for technical provisions, do we implement a fixed effects regression model, as suggested by the Hausman test (p-value = 0.0001). We thus estimate the following three models:

$$\begin{aligned} VA\ impact_{i,y} = {} & \beta_1\ Solvency\ pre\ VA_{i,y} + \sum_j \beta_j\ Sensitivity\ j_{i,y} + \beta_5\ ln(Size_{i,y}) \\ & + \beta_6\ Life_{i,y} + \alpha_i + \varepsilon_{i,y} \end{aligned} \tag{8}$$

$$MA\ impact_{i,y} = \beta_1\ Solvency\ pre\ MA_{i,y} + \sum_j \beta_j\ Sensitivity\ j_{i,y} + \beta_5\ ln(Size_{i,y}) + \beta_6\ Life_{i,y} + \alpha_i + \varepsilon_{i,y} \tag{9}$$

$$TP\ impact_{i,y} = \beta_1\ Solvency\ pre\ TP_{i,y} + \sum_j \beta_j\ Sensitivity\ j_{i,y} + \beta_5\ ln(Size_{i,y}) + \beta_6\ Life_{i,y} + u_i + \varepsilon_{i,y} \tag{10}$$

All variables in Equations (8) – (10) refer to an insurer $i$ in year $y$. $Solvency\ pre\ LTG\ k_{i,y}$ is model-specific and subtracts the value of the dependent variable from the solvency ratio (cf. Equation (7)). In each model, $\beta_1$ indicates whether the probability of using an LTG measure and the magnitude of its impact are higher for an insurer with an otherwise low solvency ratio. $Sensitivity\ j_{i,y}$ represents the estimated coefficients for the three market risks $j = \{y10, CDS, Index\}$ from the first stage of the empirical analysis. These are $\beta_{y10,i,p}$, $\beta_{CDS,i,p}$ and $\beta_{m,i,p}$ from Equation (5), which measures insurers' sensitivities to long-term interest rates, sovereign CDS spreads, and the Euro Stoxx 50 market index.[25] We control for $ln(Size_{i,y})$ and the share of life insurance reserves $Life_{i,y}$. $\alpha_i$ represents random effects, $u_{i,}$ signifies insurer fixed effects and $\varepsilon_{i,y}$ is the error term. Based on the variance inflation factors, which never exceed a value of 10 for the variables of interest, there is no evidence of multicollinearity.

In a second set of analyses, we examine the drivers of discretionary decisions regarding internal models for calculating SCR. For this purpose, we run logistic regressions with the binary variables for Solvency II modeling (cf. Table 4) as dependent variables. We assume random effects and, for the most part, we use the same independent variables as in previous models. One difference concerns the calculation of the solvency ratio without LTG measures. Since, Solvency II does not, to our knowledge, allow the effects of LTG measures to be added up, we define a variable $Solvency\ pre\ LTG1_{i,y}$ that subtracts the impact of the LTG measure with the largest effect in a given insurer-year from the solvency ratio:[26]

$$Solvency\ pre\ LTG1_{i,y} = Solvency\ Ratio_{i,y} - max\{Impact\ of\ LTG\ k_{i,y}\} \tag{11}$$

[25] We use a different notation than in Section 2 to avoid confusion between the market risk sensitivities and the coefficients of the independent variables in Equations (8) − (10). Hence, $Sensitivity\ y10_{i,y}$ corresponds to $\beta_{y10,i,p}$, $Sensitivity\ CDS_{i,y}$ corresponds to $\beta_{CDS,i,p}$ and $Sensitivity\ Index_{i,y}$ corresponds to $\beta_{m,i,p}$. Note, for example, that $Sensitivity\ j_{i,2020} = \beta_{j,i,2010-2019}$, because we use 10-year time windows to estimate the betas in the first stage of our empirical analysis (cf. Section 2.3). To avoid the problem of reverse causality in our models, we delay the end of the time window period $p$ by one year relative to the year $y$.

[26] The empirical findings for the drivers of the internal model components are robust to using the reported solvency ratio instead of $Solvency\ pre\ LTG1_{i,y}$.

The general formula for the logistic panel regressions is shown below. The dependent binary variable differs in the individual models. Thus, $Binary_{i,y}$ from Equation (12) should be replaced by the variables reflecting the individual components of the internal models ($Internal\ Model_{i,y}$, $Internal\ Interest\ Rate\ Risk_{i,y}$, $EU\ Gov\ Bond\ Spread\ Risk_{i,y}$, etc.).

$$log\frac{P(Binary_{i,y}=1)}{1-P(Binary_{i,y}=1)} = \beta_1\ Solvency\ pre\ LTG1_{i,y} + \sum_j \beta_j\ Sensitivity\ j_{i,y} + \beta_5\ ln(Size_{i,y}) + \beta_6\ Life_{i,y} + \alpha_i + \varepsilon_{i,y} \quad (12)$$

## 3.3 Results

The regression results for our empirical models investigating the determinants of the impact of each LTG measure on the solvency ratio are presented in Table 5, Table 6 and Table 7. Columns (1) – (2) show the coefficients and p-values (in parentheses) of simplified models. Column (1) is based on univariate OLS regressions with the solvency ratio excluding the respective LTG impact as the only independent variable. Column (2) extends the model in column (1) by introducing the sensitivity estimates (betas from the first stage of the empirical analysis in Section 2) as additional regressors. Column (3) additionally controls for the firm characteristics and thus corresponds to our empirical models from Equations (8) – (10).

For the volatility adjustment, the empirical results are presented in Table 5. In all three columns, the solvency ratio after removing the impact of the volatility adjustment has a highly significant influence on the dependent variable. The finding suggests that this LTG measure is used mainly by insurers with relatively lower "true" solvency ratios. The coefficient of -0.083 in column (3) means that for two otherwise identical insurance companies with solvency ratios that differ by 100ppt, the insurer with the lower value will, on average, adjust its reported solvency ratio upwards by 8.3ppt just by using the volatility adjustment.

Furthermore, the results show that a higher interest rate risk, as perceived by financial investors, has a significant effect on the impact of the LTG measure on the solvency ratio.[27] A 1ppt decrease in the sensitivity measure $Sensitivity_{y10,i,y}$ (= $\beta_{y10,i,p}$ from the first stage of the regression analysis) leads to a ceteris paribus increase in the impact of the volatility adjustment of 0.21ppt (column (3)).[28] Hence, the more insurers suffer from falling interest rates, the more likely they are to use the volatility adjustment, which then has a great impact on the solvency

[27] Note that a negative coefficient means that insurers that suffer more from falling interest rates experience a greater impact of the LTG measure on the solvency ratio.

[28] The standardized beta coefficients imply that a one standard deviation decrease in $Sensitivity_{y10,i,y}$ (0.18ppt, cf. Table 4) increases the impact of the volatility adjustment by 0.19 standard deviations (0.038ppt).

ratio. This finding can be explained by the fact that the volatility adjustment immunizes insurers against short-term changes in interest rates. Therefore, firms that are more sensitive to fluctuations in long-term yields tend to use the LTG more extensively. Our results suggest that insurers using the volatility adjustment are characterized by a wider duration gap and/or large bond investments. This finding may be of particular interest to policyholders and investors trying to extract relevant information about interest rate risk from SFCRs. Notably, the effect is still significant when controlling for the share of life insurance technical provisions.

| Dependent variable: | VA Impact$_{i,y}$ (ppt effect on Solvency) (1) | (2) | (3) |
|---|---|---|---|
| Solvency pre VA$_{i,y}$ | -0.077*** | -0.080*** | -0.083*** |
| | (0.000) | (0.000) | (0.000) |
| Sensitivity y10$_{i,y}$ | | -0.198*** | -0.208*** |
| | | (0.003) | (0.003) |
| Sensitivity CDS$_{i,y}$ | | 0.171 | 0.230 |
| | | (0.627) | (0.537) |
| Sensitivity Index$_{i,y}$ | | 0.042 | -0.032 |
| | | (0.443) | (0.626) |
| ln(Size$_{i,y}$) | | | 0.023 |
| | | | (0.106) |
| Life Share$_{i,y}$ | | | 0.149** |
| | | | (0.043) |
| No. of obs. | 233 | 232 | 225 |
| No. of insurers | 49 | 49 | 47 |
| $R^2$ within | 0.047 | 0.064 | 0.058 |
| $R^2$ overall | 0.100 | 0.206 | 0.371 |
| $R^2$ between | 0.113 | 0.230 | 0.403 |
| Standardized beta coefficients | | | |
| Sensitivity y10$_{i,y}$ | | -.18 | -.19 |

Note: Random effect regressions of insurers' annual solvency ratio impact of the volatility adjustment from 2016 to 2020. Sources: SFCRs (impact of LTG measures from QRT S.22.01.22), SNL (insurer-level size and share of life insurance reserves). Market risk sensitivity coefficients (betas) are estimated in the first stage of the regression analyses. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively. P-values are in parentheses.

*Table 5: Determinants of the impact of the volatility adjustment on the solvency ratio*

We also find that the impact of the volatility adjustment on the solvency ratio is significantly higher for life insurers. A pure life insurer adjusts its solvency ratio upwards by about 15ppt on average using the volatility adjustment compared to an otherwise identical pure non-life insurer (cf. column (3)). According to the empirical analysis, credit risk and stock market sensitivities cannot be identified as significant determinants of the impact of the volatility adjustment. The effect of $ln(Size_{i,y})$ is borderline insignificant, but the coefficient indicates that the volatility adjustment has a greater effect on the reported solvency ratio of large insurers.

The regression results for the matching adjustment are shown in Table 6. While a significant effect of $Solvency\ pre\ MA_{i,y}$ can be observed in column (1) and (2), it is borderline insignificant in column (3) after controlling for insurers' sensitivity to credit risk and their size.

Therefore, although the matching adjustment has the largest average impact on the solvency ratio of all LTGs (cf. Figure 3), we find no evidence at the 10% significance level that its impact is higher for insurers with otherwise low solvency ratios. Also, the coefficients for $Solvency\ pre\ MA_{i,y}$ are almost five times smaller than the correspondent variable $Solvency\ pre\ VA_{i,y}$ in Table 5 (-0.017 vs. -0.083).

| Dependent variable: | MA Impact$_{i,y}$ (ppt effect on Solvency) (1) | (2) | (3) |
|---|---|---|---|
| Solvency pre MA$_{i,y}$ | -0.024** | -0.021** | -0.017 |
| | (0.027) | (0.049) | (0.115) |
| Sensitivity y10$_{i,y}$ | | -0.036 | -0.019 |
| | | (0.298) | (0.609) |
| Sensitivity CDS$_{i,y}$ | | -0.594*** | -0.527*** |
| | | (0.001) | (0.007) |
| Sensitivity Index$_{i,y}$ | | 0.011 | -0.016 |
| | | (0.779) | (0.701) |
| ln(Size$_{i,y}$) | | | 0.040*** |
| | | | (0.000) |
| Life Share$_{i,y}$ | | | -0.009 |
| | | | (0.863) |
| No. of obs. | 233 | 232 | 225 |
| No. of insurers | 49 | 49 | 47 |
| $R^2$ within | 0.009 | 0.061 | 0.095 |
| $R^2$ overall | 0.386 | 0.199 | 0.206 |
| $R^2$ between | 0.420 | 0.199 | 0.218 |
| Standardized beta coefficients | | | |
| Sensitivity CDS$_{i,y}$ | | -.43 | -.37 |

Note: Random effect regressions of insurers' annual solvency ratio impact of the matching adjustment from 2016 to 2020. Sources: SFCRs (impact of LTG measures from QRT S.22.01.22), SNL (insurer-level size and share of life insurance reserves). Market risk sensitivity coefficients (betas) are estimated in the first stage of the regression analyses. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively. P-values are in parentheses.

*Table 6: Determinants of the impact of the matching adjustment on the solvency ratio*

In contrast, the empirical results verify a significant effect of the credit risk measure on the impact of the matching adjustment. A 1ppt decrease in $Sensitivity\ CDS_{i,y}$ ($= \beta_{CDS,i,p}$ from the first stage of the regression analysis in Section 2) increases the impact by 0.527ppt (column (3)), holding all other variables constant. This implies that insurers that suffer more from rising CDS spreads of domestic government debt are more likely to use the adjust and have, on average, a larger impact of the LTG on the solvency ratio. The standardized beta coefficients are about twice as high as for the volatility adjustment and $Sensitivity\ y10_{i,y}$, underscoring the important effect that the credit risk sensitivity has on the use of the matching adjustment. Ceteris paribus, an insurer with a one standard deviation lower $Sensitivity\ CDS_{i,y}$ (0.03ppt, cf. Table 4) experiences a 0.37 standard deviation higher impact of the matching adjustment (0.0962ppt). The effect of the credit risk sensitivities is reasonable considering that the matching adjustment typically reduces the capital requirements for spread and concentration risk and thus leads to a decrease in the SCR. As a result, insurers with greater credit risk sensitivities, e.g., due to riskier assets, have a higher incentive to use this LTG measure. The large average impact of the matching adjustment on the solvency ratio is, however, disproportionate to the extent of interest rate risk and sovereign credit risk estimated based on market data. This discrepancy suggests that the weighting of the modules for the SCR calibration does not optimally reflect the true market risk profiles of insurers and that the ability to use LTG measures may introduce systemic bias.

Moreover, empirical results in column (3) of Table 6 indicate that the impact of the matching adjustment on the solvency ratio is significantly more pronounced for larger insurers. This effect is highly significant and is particularly related to the high regulatory requirements associated with the use of the LTG in terms of adequate duration matching and additional reporting. Only large insurers have the necessary capacity to meet the requirements set out in Article 77c of the European Commission (2009) and obtain supervisory approval.

In Table 7, we examine the impact of the transitional for technical provisions, which can only be used temporarily and allows insurers to gradually adjust to the changes in the calculation of capital reserves from Solvency I to Solvency II until the year 2032. The coefficient of the solvency ratio calculated without the LTG measure, $Solvency\ pre\ TP_{i,y}$, is negative and highly significant in all models. Therefore, more solvent insurers are less likely to use the LTG measure. According to column (3), which corresponds to the model presented in Equation (10), for two otherwise equal insurers with a solvency ratio that differs by 100ppt, the less solvent insurer will use the transitional to adjust its solvency ratio upward by 10ppt on average.

As for the volatility adjustment, the coefficient of $Sensitivity\ y10_{i,y}$ is negative and significant for the transitional on technical provisions (cf. columns (2) and (3)). This result indicates that insurers facing higher interest rate risk tend to use the transitional more frequently and experience a larger effect than insurers less exposed to falling interest rates. However, the standardized beta coefficients in column (3) of Table 7 are smaller (-0.14 vs. -0.19) and the p-values are larger (0.003 vs. -0.166) compared to Table 5. This implies that insurers' sensitivity to interest rates is a more relevant determinant of the impact of the volatility adjustment than of the transitional for technical provisions. In other words, insurers suffering from falling interest rates are more likely to use the volatility adjustment than the transitional. For the other market risk sensitivities and insurer characteristics, we do not observe a significant effect on the impact of the transitional on the solvency ratio.

| Dependent variable: | TP Impact$_{i,y}$ (ppt effect on Solvency) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Solvency pre TP$_{i,y}$ | -0.090*** | -0.096*** | -0.100*** |
| | (0.000) | (0.000) | (0.000) |
| Sensitivity y10$_{i,y}$ | | -0.144* | -0.166* |
| | | (0.077) | (0.059) |
| Sensitivity CDS$_{i,y}$ | | 0.040 | -0.059 |
| | | (0.926) | (0.898) |
| Sensitivity Index$_{i,y}$ | | 0.028 | 0.023 |
| | | (0.777) | (0.821) |
| ln(Size$_{i,y}$) | | | -0.051 |
| | | | (0.143) |
| Life Share$_{i,y}$ | | | 0.077 |
| | | | (0.613) |
| No. of obs. | 233 | 232 | 225 |
| No. of insurers | 49 | 49 | 47 |
| $R^2$ within | 0.074 | 0.091 | 0.108 |
| $R^2$ overall | 0.053 | 0.007 | 0.036 |
| $R^2$ between | 0.043 | 0.002 | 0.061 |
| Standardized beta coefficients | | | |
| Sensitivity y10$_{i,y}$ | | -.13 | -.14 |

Note: Firm fixed effect regressions of insurers' annual solvency ratio impact of the transitional on technical provisions from 2016 to 2020. Sources: SFCRs (impact of LTG measures from QRT S.22.01.22), SNL (insurer-level size and share of life insurance reserves). Market risk sensitivity coefficients (betas) are estimated in the first stage of the regression analyses. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively. P-values are shown in parentheses.

*Table 7: Determinants of the impact of the transitional on technical provisions on the solvency ratio*

Overall, our findings suggest that insurers are strategically using LTG measures in a way that exploits the discretion to optimize the reported solvency ratio and to mask their own risk drivers. This is evidenced by the results that the average impact of each LTG is higher for insurers with otherwise lower solvency ratios and for insurers with relatively greater sensitivities to either long-term interest rates or sovereign CDS spreads. In particular, insurers with large market risk exposures use the LTG measures to make their SCRs less sensitive to these risks and to better present themselves to the public through higher solvency ratios.

In addition to the LTG measures, we examine discretionary choices in the composition of internal models for calculating the SCR under Solvency II. Table 8 presents the results of the logistic regressions defined in Equation (12). Unlike previous regression tables, we now use binary dependent variables that differ in each column. Additional results from the logistic regressions for other dependent variables, including $Internal\ Market\ Risk_{i,y}$ and $Internal\ Default\ Risk_{i,y}$ are presented in Table A6 in Appendix V.

In column (1) of Table 8, the dependent variable is $Internal\ Model_{i,y}$ which equals one if an insurer uses a partial or full internal model to calculate its SCR. The regression coefficients show that the probability of choosing an internal model is significantly higher for more solvent insurers, those with lower credit risk sensitivities, those with higher stock market sensitivities and for larger insurers. Overall, these results seem plausible. First, more solvent and larger insurers may be characterized by more complex risk profiles that necessitate the use of an internal model to comply with Solvency II requirements; at the same time, these insurers may be able to take better advantage of economies of scale when implementing internal models. Second, insurers using internal models may already have more diversified investments or better immunization strategies and thus less exposure to sovereign credit risk (measured by a small negative or even positive value of $Sensitivity\ CDS_{i,y}$). Third, higher stock market sensitivities $Sensitivity\ Index_{i,y}$ ($= \beta_{m,i,p}$ from the first stage of the regression analysis in Section 2) are indicative of high CAPM betas, which imply higher cost of capital and thus a greater incentive to reduce the SCR using an internal model.

| | Internal Model$_{i,y}$ (1) | Internal Interest Rate Risk$_{i,y}$ (2) | EU Gov Bond Spread Risk$_{i,y}$ (3) |
|---|---|---|---|
| Solv. pre LTG1$_{i,y}$ | 8.634*** | 3.703 | 3.894 |
| | (0.000) | (0.167) | (0.246) |
| Sensitivity y10$_{i,y}$ | 7.006 | 28.035*** | -2.277 |
| | (0.448) | (0.009) | (0.808) |
| Sensitivity CDS$_{i,y}$ | 130.390*** | 317.966*** | 45.524 |
| | (0.005) | (0.000) | (0.304) |
| Sensitivity Index$_{i,y}$ | 28.950** | 16.303** | 16.459** |
| | (0.013) | (0.038) | (0.036) |
| ln(Size$_{i,y}$) | 3.701*** | 9.808*** | 9.879*** |
| | (0.001) | (0.000) | (0.000) |
| Life Share$_{i,y}$ | -9.269 | -15.407*** | 3.071 |
| | (0.194) | (0.003) | (0.742) |
| No. of obs. | 225 | 225 | 225 |
| No. of insurers | 47 | 47 | 47 |
| Wald chi$^2$ | 40.800 | 71.550 | 35.645 |
| Log likelihood | -44.279 | -29.305 | -13.581 |
| Sigma | 15.171 | 17.326 | 12.466 |
| Rho | 0.986 | 0.989 | 0.979 |

Note: Logarithmic regressions of insurers' annual use of internal models from 2016 to 2020 with random effects. Sources: SFCRs (qualitative information on internal models from Section E.4 and solvency ratio from QRT S.22.01.22), SNL (insurer-level size and share of life insurance reserves). Market risk sensitivity coefficients (betas) are estimated in the first stage of the regression analyses. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively. P-values are shown in parentheses.

*Table 8: Determinants of internal models*

In column (2), we investigate the drivers of insurers' decision to replace the standard formula's interest rate risk submodule, which is part of the market risk module, with a (partial) internal model. This replacement is more likely for insurers with lower interest rate risk and credit risk sensitivities, possibly because these firms are capable of finding strategies to immunize against market movements. In addition, internal interest rate risk modules are more likely for non-life insurers, an insurer type with typically low interest rate exposures. These findings suggest that internal models are more likely to be used for risks to which insurers do not have large exposures. This is also supported by the results shown in Table A6, which emphasize that insurers with low exposure to sovereign credit risk are significantly more likely to model the spread risk submodule internally (cf. column (2)), and that non-life insurers are more likely to model counterparty default risk internally (cf. column (3)). As with internal models in general, the decision to model interest rate risk internally is also significantly associated with greater stock market sensitivity and size.

Finally, we analyze the likelihood of including the spread risk stemming from EU government bonds in an internal model, even though these investments are exempt from spread and default risk under Solvency II. Our empirical results in column (3) of Table 8 show that the probability increases significantly with an insurer's stock market sensitivity and size. Notably, these are both factors that also lead to increased regulatory attention. Presumably, large insurers in particular take into account all potential market risks in their SCR calculation, so that their true risk profile is reflected in the SCR. Similarly, the probability of including the default risk of EU sovereign debt significantly increases with insurers' size (cf. column (4) of Table A6).

## 3.4 Robustness

The empirical results are robust to several adjustments. In particular, we perform the following set of robustness tests against the original specifications in Equations (8), (9) and (10). An overview of the corresponding regression results is presented in Table A5 in Appendix IV.

1. We use t-values instead of betas to estimate insurers' sensitivities to interest rates, CDS spreads, and the stock market index. High absolute t-values demonstrate the statistical significance of a relationship with an insurer's stock performance.
2. We use 5-year time windows instead of 10-year time windows to estimate insurers' market risk sensitivities in the first stage of the empirical analysis.
3. We use weighted CDS returns based on insurers' country-specific investments instead of measuring sensitivities to national sovereign CDS spreads.[29]
4. We use national stock indices to estimate insurers' stock market sensitivities instead of using the Euro Stoxx 50 index for all insurers.
5. We winsorize stock returns in the first stage of the regression analysis (cf. Equation (5)) at the 0.5% and 99.5% levels.[30]

[29] For this robustness test, we use asset allocation data from EIOPA (2023) in line with Grochola et al. (2023).
[30] The highest 0.5% of stock return observations are thus downgraded to the 99.5% quantile and the lowest 0.5% of stock return observations are upgraded to the 0.5% quantile.

6. We winsorize the estimated sensitivity coefficients (betas) for the second stage of the empirical analysis (cf. Equations (8), (9) and (10)) at the 0.5% and 99.5% levels to ensure that the results are not driven by extreme outliers.
7. We include in the sample five micro-cap insurers with less than $250 million in total assets as of year-end 2020. While our empirical results are less significant for this subset, they still hold for this expanded sample.

# 4 Conclusion

One of the main objectives of Solvency II is to provide a fair view of the risk and solvency position of European insurers. For this aim, the regulatory framework takes an economic and risk-based approach with the solvency ratio as the central outcome of Pillar I. Nevertheless, insurers have some leeway in the implementation of Solvency II, allowing them to use internal models and to adjust their reported solvency ratio upwards by using LTG measures. This paper examines the drivers of insurers' discretionary decisions and their impact on the solvency ratio.

To address the research question, we measure the market risk sensitivities of stock listed insurers and compare the estimated risk profiles with relevant information in SFCRs. By performing multivariate regression analyses at the insurer-level, we are able to reproduce the results of previous papers with respect to interest rate risk and credit risk (cf. Berends et al. (2013), Hartley et al. (2017), Düll et al. (2017)). This implies that we find a negative effect of falling interest rates and of rising sovereign CDS spreads on insurers' stock prices. The beta coefficients obtained from the market data analysis serve as sensitivity estimates for interest rate risk, credit risk, and stock market sensitivities.

After systematically analyzing the SFCRs from 2016 to 2020, we find that insurers optimize their reported solvency situation by making discretionary decisions that reduce capital requirements for material risk drivers. For instance, the use of the volatility adjustment, applied by 69% of the insurers in our sample, is positively related to the interest rate risk as perceived by financial markets, even when controlling for the share of life insurance in technical provisions. Similarly, the matching adjustment, which lowers the SCR for spread risk, is associated with significantly higher credit risk sensitivities. The matching adjustment has the largest average impact on the solvency ratio when applied (59ppt), even though market data indicate that interest rate risk is more relevant for European insurers.

In addition, both the volatility adjustment and the transitional for technical interest rates are used mainly by insurers with otherwise low reported solvency ratios. The LTG measures thus appear to provide a regulatory loophole to avoid higher SCR that would be appropriate under a market-oriented risk management approach. While Solvency II aims to provide a risk-based economic approach, the LTG measures prevent the SFCRs from providing a stand-alone figure that transparently informs about insurers' risk exposures and solvency position. Instead, our empirical results suggest that the implementation of LTGs may lead to adverse selection in a manner similar to the banking sector.

Finally, our hand-collected data on the composition of internal models shows that insurers tend to model internally those risks for which they have already established effective immunization strategies. Moreover, internal models are primarily used by large insurance companies, which are subject to more regulatory and public scrutiny.

# Appendix

## I. Descriptive statistics

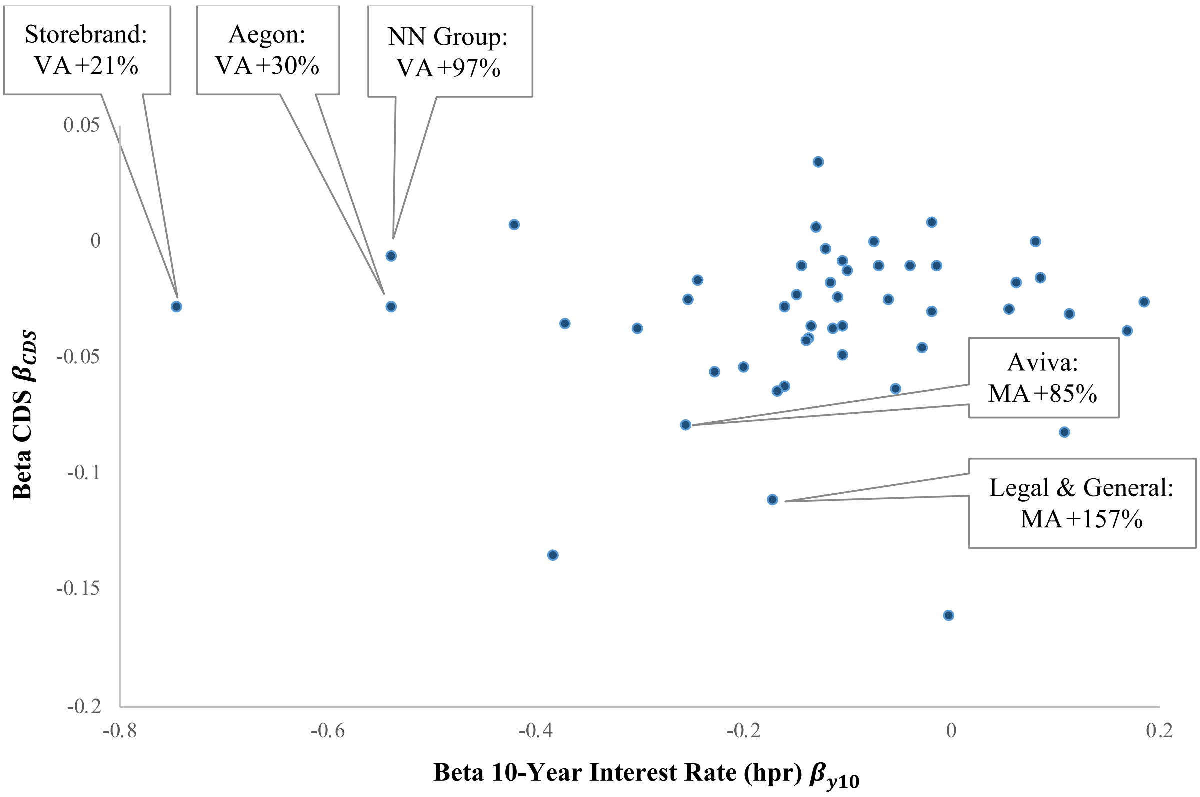
| Name | Country | First day in sample | Last day in sample | Mean stock returns | SD stock returns | Min. stock return | Max. stock return |
|---|---|---|---|---|---|---|---|
| UNIQA Insurance Group AG | Austria | 20.03.06 | 30.12.19 | 0.00% | 1.69% | -15.88% | 9.96% |
| Vienna Insurance Group AG | Austria | 20.03.06 | 30.12.19 | 0.01% | 2.08% | -17.93% | 16.26% |
| Ageas SA | Belgium | 20.03.06 | 30.12.19 | 0.04% | 2.70% | -26.47% | 29.54% |
| KBC Groep NV | Belgium | 20.03.06 | 30.12.19 | 0.05% | 3.26% | -24.92% | 49.91% |
| Alm Brand A/S | Denmark | 20.03.06 | 30.12.19 | 0.01% | 2.26% | -21.17% | 28.30% |
| Topdanmark A/S | Denmark | 20.03.06 | 30.12.19 | 0.06% | 1.55% | -9.48% | 15.11% |
| Tryg A/S | Denmark | 20.03.06 | 30.12.19 | 0.06% | 1.46% | -12.73% | 7.75% |
| Sampo Plc | Finland | 20.03.06 | 30.12.19 | 0.06% | 1.57% | -16.67% | 10.72% |
| Axa SA | France | 20.03.06 | 30.12.19 | 0.04% | 2.44% | -18.41% | 21.87% |
| CNP Assurances SA | France | 20.03.06 | 30.12.19 | 0.03% | 1.77% | -13.45% | 11.73% |
| Coface SA | France | 27.06.14 | 30.12.19 | 0.04% | 2.00% | -29.73% | 11.61% |
| Scor SE | France | 20.03.06 | 30.12.19 | 0.05% | 1.69% | -11.42% | 14.50% |
| Allianz SE | Germany | 20.03.06 | 30.12.19 | 0.05% | 1.88% | -12.99% | 19.49% |
| Muenchener Rueck AG | Germany | 20.03.06 | 30.12.19 | 0.05% | 1.45% | -10.54% | 15.62% |
| Nürnberger Beteiligungs AG | Germany | 20.03.06 | 30.12.19 | 0.05% | 1.74% | -14.72% | 25.40% |
| Rheinland Holding AG | Germany | 20.03.06 | 30.12.19 | 0.10% | 3.41% | -19.35% | 19.51% |
| Talanx AG | Germany | 02.10.12 | 30.12.19 | 0.07% | 1.34% | -6.57% | 5.23% |
| Wuestenrot & Wuerttem. AG | Germany | 20.03.06 | 30.12.19 | 0.02% | 1.81% | -13.22% | 13.86% |
| European Reliance Gen. Ins. | Greece | 20.03.06 | 30.12.19 | 0.12% | 3.06% | -17.14% | 19.61% |
| FBD Holdings PLC | Ireland | 20.03.06 | 30.12.19 | -0.01% | 2.27% | -25.08% | 20.03% |
| Assicurazioni Generali SpA | Italy | 20.03.06 | 30.12.19 | 0.01% | 1.72% | -16.77% | 13.10% |
| Societa Cattolica di Assic. Sc | Italy | 20.03.06 | 30.12.19 | -0.01% | 1.92% | -17.43% | 17.30% |
| UnipolSai Assicurazioni SpA | Italy | 20.03.06 | 30.12.19 | 0.00% | 4.05% | -58.82% | 119.81% |
| Vittoria Assicurazioni SpA | Italy | 20.03.06 | 25.09.18 | 0.05% | 1.67% | -10.80% | 19.73% |
| Aegon NV | Netherl. | 20.03.06 | 30.12.19 | 0.02% | 2.80% | -24.18% | 35.28% |
| ASR Nederland NV | Netherl. | 10.06.16 | 30.12.19 | 0.08% | 1.36% | -7.43% | 6.76% |
| Delta Lloyd NV | Netherl. | 22.02.10 | 23.12.16 | 0.22% | 2.92% | -7.93% | 10.78% |
| NN Group NV | Netherl. | 02.07.14 | 30.12.19 | 0.06% | 1.34% | -8.03% | 8.77% |
| Gjensidige Forsikring ASA | Norway | 10.12.10 | 30.12.19 | 0.09% | 1.26% | -10.31% | 12.28% |
| Protector Forsikring ASA | Norway | 25.05.07 | 30.12.19 | 0.12% | 2.63% | -22.39% | 24.98% |
| Storebrand ASA | Norway | 20.03.06 | 30.12.19 | 0.05% | 2.83% | -19.55% | 27.95% |
| Powszechny Zaklad Ubez. SA | Poland | 12.05.10 | 30.12.19 | 0.03% | 1.49% | -6.59% | 7.27% |
| Pozavarovalnica Sava dd | Slovenia | 12.06.08 | 30.12.19 | 0.05% | 2.24% | -11.36% | 14.91% |
| Zavarovalnica Triglav dd | Slovenia | 09.09.08 | 30.12.19 | 0.03% | 1.78% | -10.20% | 8.91% |
| Grupo Catalana Occidente SA | Spain | 20.03.06 | 30.12.19 | 0.04% | 2.03% | -8.42% | 13.26% |
| Mapfre SA | Spain | 20.03.06 | 30.12.19 | 0.03% | 2.08% | -12.58% | 17.11% |
| Admiral Group PLC | UK | 20.03.06 | 30.12.19 | 0.08% | 1.88% | -25.61% | 25.50% |
| Aviva PLC | UK | 20.03.06 | 30.12.19 | 0.03% | 2.43% | -33.37% | 25.10% |
| Beazley PLC | UK | 20.03.06 | 30.12.19 | 0.09% | 1.82% | -13.10% | 14.58% |
| Chesnara PLC | UK | 20.03.06 | 30.12.19 | 0.07% | 2.03% | -14.51% | 11.09% |
| Direct Line Insurance Group | UK | 11.10.12 | 30.12.19 | 0.07% | 1.21% | -7.16% | 12.62% |
| Hansard Global PLC | UK | 13.12.06 | 30.12.19 | 0.01% | 2.28% | -14.36% | 20.10% |
| Legal & General Group PLC | UK | 20.03.06 | 30.12.19 | 0.07% | 2.40% | -28.88% | 27.51% |
| Old Mutual PLC | UK | 20.03.06 | 29.12.17 | 0.06% | 2.68% | -21.60% | 30.33% |
| Phoenix Group Holdings | UK | 18.11.09 | 30.12.19 | 0.05% | 1.49% | -11.54% | 11.17% |
| Prudential PLC | UK | 20.03.06 | 28.12.18 | 0.07% | 2.58% | -20.00% | 23.46% |
| RSA Insurance Group PLC | UK | 20.03.06 | 30.12.19 | 0.03% | 1.71% | -20.84% | 18.43% |
| St. James's Place PLC | UK | 20.03.06 | 30.12.19 | 0.07% | 2.18% | -16.18% | 27.05% |
| Standard Life Aberdeen PLC | UK | 10.07.06 | 29.12.17 | 0.06% | 2.21% | -17.31% | 20.51% |

*Table A1: Stock returns on insurer level*

| | N | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|---|
| **Robustness equity risk variables (country-day level level in ppt)** | | | | | | |
| $r_{m,c,t}$ (Index return, all countries) | 51,342 | 0.012 | 0.05 | 1.43 | -33.21 | -49.89 |
| $r_{m,Austria,t}$ (Index return) | 3,302 | 0.000 | 0.04 | 1.54 | -9.74 | 12.77 |
| $r_{m,Belgium,t}$ (Index return) | 3,489 | 0.005 | 0.03 | 1.22 | -7.98 | 9.96 |
| $r_{m,Denmark,t}$ (Index return) | 3,371 | 0.032 | 0.08 | 1.29 | -11.06 | 9.73 |
| $r_{m,Finland,t}$ (Index return) | 3,399 | 0.024 | 0.04 | 1.40 | -8.52 | 9.73 |
| $r_{m,France,t}$ (Index return) | 3,491 | 0.013 | 0.04 | 1.38 | -9.04 | 11.18 |
| $r_{m,Germany,t}$ (Index return) | 3,455 | 0.017 | 0.07 | 1.34 | -7.23 | 11.40 |
| $r_{m,Greece,t}$ (Index return) | 3,338 | -0.018 | 0.04 | 1.96 | -13.42 | 14.37 |
| $r_{m,Ireland,t}$ (Index return) | 3,425 | 0.009 | 0.03 | 1.45 | -13.03 | 10.22 |
| $r_{m,Italy,t}$ (Index return) | 3,467 | -0.005 | 0.04 | 1.58 | -12.48 | 11.49 |
| $r_{m,Netherlands,t}$ (Index return) | 3,519 | 0.016 | 0.05 | 1.29 | -9.14 | 10.55 |
| $r_{m,Norway,t}$ (Index return) | 3,395 | 0.037 | 0.08 | 1.56 | -10.66 | 11.65 |
| $r_{m,Poland,t}$ (Index return) | 3,385 | 0.018 | 0.04 | 1.20 | -7.95 | 6.27 |
| $r_{m,Slovenia,t}$ (Index return) | 3,411 | 0.008 | 0.01 | 1.47 | -33.21 | 49.89 |
| $r_{m,Spain,t}$ (Index return) | 3,475 | 0.003 | 0.05 | 1.47 | -12.35 | 14.43 |
| $r_{m,UK,t}$ (Index return) | 3,420 | 0.015 | 0.04 | 1.15 | -8.85 | 9.84 |

*Table A2:* *National stock index returns on country level*

## II. Estimated market risk sensitivities (betas)




Note: "VA" ("MA") stands for "volatility adjustment" ("matching adjustment"). The number after "VA" or "MA" indicates the impact of the respective LTG measure on the solvency ratio of a given insurer in the year 2019. Each dot reflects an insurer's estimated regression coefficients $\beta_{y10}$ and $\beta_{CDS}$ from Equation (5) over the period from 2009 to 2018. A company on the lower left would substantially suffer from falling interest rates and from rising default probabilities of domestic sovereign debt.

*Figure A1:* *Insurer-specific estimates for sensitivities to interest rate and CDS fluctuation*

| Sensitivities (betas) | | 2006-2015 | | | 2007-2016 | | | 2008-2017 | | | 2009-2018 | | | 2010-2019 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Name** | **Country** | **y10** | **CDS** | **Index** | **y10** | **CDS** | **Index** | **y10** | **CDS** | **Index** | **y10** | **CDS** | **Index** | **y10** | **CDS** | **Index** |
| UNIQA Insurance Group AG | Austria | -0.09 | -0.02 | 0.32 | -0.12 | -0.02 | 0.35 | -0.17 | -0.02 | 0.35 | -0.13 | 0.01 | 0.41 | -0.14 | 0.01 | 0.46 |
| Vienna Insurance Group AG | Austria | 0.03 | -0.05 | 0.82 | -0.01 | -0.05 | 0.83 | -0.07 | -0.04 | 0.84 | -0.14 | -0.04 | 0.80 | -0.18 | -0.03 | 0.72 |
| Ageas SA | Belgium | -0.38 | -0.15 | 1.14 | -0.39 | -0.14 | 1.11 | -0.40 | -0.15 | 1.10 | -0.38 | -0.14 | 0.99 | -0.26 | -0.11 | 0.98 |
| KBC Groep NV | Belgium | 0.08 | -0.15 | 1.40 | 0.03 | -0.14 | 1.39 | -0.01 | -0.15 | 1.39 | 0.00 | -0.16 | 1.36 | -0.31 | -0.12 | 1.22 |
| Alm Brand A/S | Denmark | -0.12 | -0.02 | 0.62 | -0.09 | -0.03 | 0.61 | -0.08 | -0.03 | 0.60 | 0.06 | -0.03 | 0.56 | 0.02 | 0.00 | 0.53 |
| Topdanmark A/S | Denmark | -0.11 | -0.01 | 0.56 | -0.10 | -0.02 | 0.56 | -0.07 | -0.01 | 0.55 | -0.10 | -0.01 | 0.48 | -0.10 | -0.01 | 0.46 |
| Tryg A/S | Denmark | -0.23 | 0.00 | 0.46 | -0.19 | -0.01 | 0.48 | -0.18 | -0.01 | 0.47 | -0.12 | 0.00 | 0.47 | -0.05 | 0.00 | 0.48 |
| Sampo Plc | Finland | -0.27 | -0.03 | 0.74 | -0.25 | -0.03 | 0.73 | -0.27 | -0.04 | 0.72 | -0.11 | -0.04 | 0.77 | -0.16 | -0.03 | 0.72 |
| Axa SA | France | -0.22 | -0.03 | 1.49 | -0.28 | -0.03 | 1.48 | -0.32 | -0.03 | 1.48 | -0.37 | -0.04 | 1.39 | -0.47 | -0.06 | 1.26 |
| CNP Assurances SA | France | -0.32 | -0.04 | 0.71 | -0.31 | -0.04 | 0.72 | -0.32 | -0.04 | 0.71 | -0.25 | -0.03 | 0.81 | -0.24 | -0.03 | 0.85 |
| Coface SA | France | -0.11 | -0.02 | 0.31 | -0.22 | -0.02 | 0.45 | -0.25 | -0.02 | 0.47 | -0.24 | -0.02 | 0.50 | -0.28 | -0.02 | 0.48 |
| Scor SE | France | -0.22 | -0.02 | 0.65 | -0.22 | -0.02 | 0.66 | -0.21 | -0.02 | 0.64 | -0.14 | -0.01 | 0.63 | -0.16 | -0.01 | 0.68 |
| Allianz SE | Germany | 0.05 | -0.02 | 1.09 | 0.02 | -0.02 | 1.07 | 0.03 | -0.02 | 1.07 | -0.04 | -0.01 | 1.00 | -0.09 | -0.01 | 0.94 |
| Muenchener Rueck AG | Germany | 0.02 | 0.00 | 0.73 | 0.04 | 0.00 | 0.74 | 0.05 | 0.00 | 0.74 | 0.08 | 0.00 | 0.75 | 0.05 | -0.01 | 0.71 |
| Nürnberger Beteiligungs AG | Germany | 0.06 | -0.03 | 0.08 | 0.06 | -0.03 | 0.08 | 0.04 | -0.03 | 0.07 | -0.01 | -0.01 | 0.06 | -0.04 | 0.00 | 0.11 |
| Rheinland Holding AG | Germany | -0.32 | 0.03 | 0.07 | -0.12 | 0.02 | 0.10 | -0.07 | 0.03 | 0.10 | -0.13 | 0.03 | 0.02 | -0.05 | 0.04 | 0.03 |
| Talanx AG | Germany | 0.07 | -0.01 | 0.61 | 0.03 | -0.01 | 0.66 | -0.04 | -0.01 | 0.65 | -0.07 | 0.00 | 0.66 | -0.10 | 0.00 | 0.65 |
| Wuestenrot & Wuerttem. AG | Germany | 0.09 | -0.03 | 0.27 | 0.07 | -0.03 | 0.28 | 0.03 | -0.03 | 0.27 | -0.07 | -0.01 | 0.22 | -0.11 | -0.01 | 0.25 |
| European Reliance Gen. Ins. | Greece | -0.14 | -0.02 | 0.35 | -0.05 | -0.02 | 0.35 | 0.03 | -0.02 | 0.33 | 0.09 | -0.02 | 0.31 | -0.05 | -0.01 | 0.28 |
| FBD Holdings Plc | Ireland | -0.10 | -0.04 | 0.36 | -0.12 | -0.04 | 0.35 | -0.18 | -0.03 | 0.34 | -0.16 | -0.03 | 0.32 | -0.12 | -0.03 | 0.33 |
| Assicurazioni Generali SpA | Italy | -0.17 | -0.06 | 0.84 | -0.21 | -0.06 | 0.87 | -0.25 | -0.07 | 0.86 | -0.23 | -0.06 | 0.99 | -0.24 | -0.06 | 0.97 |
| Societa Cattolica di Assic. Sc | Italy | -0.10 | -0.05 | 0.66 | -0.13 | -0.06 | 0.67 | -0.18 | -0.06 | 0.67 | -0.16 | -0.06 | 0.67 | -0.19 | -0.07 | 0.61 |
| UnipolSai Assicurazioni SpA | Italy | 0.02 | -0.07 | 0.89 | -0.01 | -0.07 | 0.91 | -0.05 | -0.07 | 0.90 | -0.05 | -0.06 | 0.95 | -0.05 | -0.07 | 0.93 |
| Vittoria Assicurazioni SpA | Italy | -0.11 | -0.04 | 0.41 | -0.13 | -0.04 | 0.40 | -0.15 | -0.04 | 0.39 | -0.11 | -0.02 | 0.42 | -0.15 | -0.01 | 0.41 |
| Aegon NV | Netherl. | -0.28 | -0.04 | 1.47 | -0.35 | -0.04 | 1.45 | -0.44 | -0.04 | 1.46 | -0.54 | -0.03 | 1.39 | -0.68 | -0.02 | 1.16 |
| ASR Nederland NV | Netherl. | NA | NA | NA | -0.46 | 0.05 | 0.63 | -0.38 | 0.02 | 0.63 | -0.42 | 0.01 | 0.68 | -0.46 | 0.01 | 0.73 |
| Delta Lloyd NV | Netherl. | -0.31 | -0.04 | 1.15 | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| NN Group NV | Netherl. | -0.42 | 0.03 | 0.41 | -0.39 | -0.03 | 0.58 | -0.52 | -0.01 | 0.59 | -0.54 | -0.01 | 0.63 | -0.57 | 0.00 | 0.65 |
| Gjensidige Forsikring ASA | Norway | 0.05 | -0.02 | 0.43 | 0.04 | -0.01 | 0.45 | 0.02 | 0.00 | 0.45 | -0.02 | 0.01 | 0.47 | -0.04 | 0.01 | 0.46 |
| Protector Forsikring ASA | Norway | 0.17 | -0.04 | 0.30 | 0.09 | -0.04 | 0.31 | 0.11 | -0.06 | 0.28 | 0.19 | -0.03 | 0.41 | 0.07 | 0.02 | 0.41 |
| Storebrand ASA | Norway | -0.68 | 0.00 | 1.15 | -0.72 | 0.00 | 1.13 | -0.78 | -0.01 | 1.13 | -0.74 | -0.03 | 1.06 | -0.93 | -0.04 | 0.99 |
| Powszechny Zaklad Ubez. SA | Poland | -0.14 | -0.08 | 0.33 | -0.17 | -0.08 | 0.33 | -0.17 | -0.07 | 0.34 | -0.17 | -0.07 | 0.37 | -0.14 | -0.06 | 0.38 |
| Pozavarovalnica Sava dd | Slovenia | 0.30 | -0.04 | 0.27 | 0.23 | -0.05 | 0.25 | 0.24 | -0.04 | 0.26 | 0.11 | -0.08 | 0.08 | 0.18 | -0.08 | 0.08 |
| Zavarovalnica Triglav dd | Slovenia | -0.26 | -0.05 | 0.17 | -0.23 | -0.05 | 0.16 | -0.24 | -0.05 | 0.16 | -0.20 | -0.05 | 0.08 | -0.12 | -0.05 | 0.07 |
| Grupo Catalana Occidente SA | Spain | -0.14 | -0.06 | 0.71 | -0.16 | -0.06 | 0.71 | -0.15 | -0.06 | 0.70 | -0.14 | -0.04 | 0.77 | -0.15 | -0.04 | 0.76 |
| Mapfre SA | Spain | -0.08 | -0.06 | 0.92 | -0.10 | -0.06 | 0.94 | -0.15 | -0.06 | 0.94 | -0.10 | -0.05 | 0.99 | -0.17 | -0.05 | 0.99 |
| Admiral Group PLC | UK | -0.26 | -0.01 | 0.62 | -0.20 | -0.01 | 0.61 | -0.17 | -0.01 | 0.57 | -0.10 | -0.01 | 0.52 | -0.12 | -0.02 | 0.52 |
| Aviva PLC | UK | -0.34 | -0.03 | 1.17 | -0.37 | -0.05 | 1.17 | -0.35 | -0.07 | 1.14 | -0.26 | -0.08 | 1.11 | -0.27 | -0.07 | 0.96 |
| Beazley PLC | UK | -0.14 | -0.01 | 0.57 | -0.08 | 0.00 | 0.58 | -0.09 | -0.01 | 0.54 | -0.11 | -0.02 | 0.45 | 0.08 | -0.02 | 0.46 |
| Chesnara PLC | UK | -0.17 | -0.01 | 0.25 | -0.14 | -0.01 | 0.26 | -0.07 | -0.02 | 0.25 | -0.06 | -0.03 | 0.20 | -0.07 | -0.02 | 0.26 |
| Direct Line Insurance Group | UK | -0.08 | -0.04 | 0.34 | -0.13 | -0.05 | 0.39 | -0.12 | -0.04 | 0.39 | -0.13 | -0.04 | 0.40 | -0.17 | -0.04 | 0.41 |
| Hansard Global PLC | UK | 0.22 | -0.03 | 0.22 | 0.16 | -0.03 | 0.20 | 0.16 | -0.04 | 0.17 | 0.11 | -0.03 | 0.18 | 0.08 | -0.04 | 0.13 |
| Legal & General Group PLC | UK | -0.13 | -0.04 | 1.05 | -0.17 | -0.06 | 1.06 | -0.14 | -0.09 | 1.02 | -0.17 | -0.11 | 0.99 | -0.26 | -0.09 | 0.84 |
| Old Mutual PLC | UK | 0.09 | -0.02 | 1.22 | 0.16 | -0.03 | 1.21 | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| Phoenix Group Holdings | UK | 0.10 | -0.01 | 0.39 | 0.12 | -0.03 | 0.44 | 0.08 | -0.03 | 0.44 | 0.06 | -0.02 | 0.46 | 0.03 | -0.01 | 0.49 |
| Prudential PLC | UK | -0.06 | -0.01 | 1.24 | -0.13 | -0.02 | 1.24 | -0.12 | -0.03 | 1.21 | NA | NA | NA | NA | NA | NA |
| RSA Insurance Group PLC | UK | -0.16 | 0.00 | 0.66 | -0.16 | -0.01 | 0.64 | -0.15 | -0.01 | 0.62 | -0.15 | -0.02 | 0.53 | -0.15 | -0.03 | 0.53 |
| St. James's Place PLC | UK | -0.20 | 0.00 | 0.86 | -0.21 | -0.01 | 0.87 | -0.19 | -0.02 | 0.83 | -0.02 | -0.03 | 0.83 | -0.05 | -0.05 | 0.84 |
| Standard Life Aberdeen PLC | UK | -0.03 | -0.01 | 0.99 | -0.07 | -0.01 | 1.02 | NA | NA | NA | NA | NA | NA | NA | NA | NA |

*Table A3: Estimated sensitivity coefficients (beta) on the insurer level*

# III. Data collected from SFCRs

| Firm name | Country | Year | LTGs Used | Solvency Reported | VA Impact | MA Impact | TP Impact | IR Impact | Model for SCR calculation |
|---|---|---|---|---|---|---|---|---|---|
| UNIQA Insurance Group AG | Austria | 2016 | 1 | 202% | 8% | 0% | 0% | 0% | Standard Formula |
| UNIQA Insurance Group AG | Austria | 2017 | 1 | 250% | 2% | 0% | 0% | 0% | Partial Internal |
| UNIQA Insurance Group AG | Austria | 2018 | 1 | 248% | 21% | 0% | 0% | 0% | Partial Internal |
| UNIQA Insurance Group AG | Austria | 2019 | 1 | 216% | 36% | 0% | 0% | 0% | Partial Internal |
| UNIQA Insurance Group AG | Austria | 2020 | 1 | 170% | 40% | 0% | 0% | 0% | Partial Internal |
| Vienna Insurance Group AG | Austria | 2016 | 1 | 195% | 9% | 0% | 0% | 0% | Partial Internal |
| Vienna Insurance Group AG | Austria | 2017 | 1 | 220% | 4% | 0% | 0% | 0% | Partial Internal |
| Vienna Insurance Group AG | Austria | 2018 | 1 | 239% | 5% | 0% | 0% | 0% | Partial Internal |
| Vienna Insurance Group AG | Austria | 2019 | 1 | 210% | 5% | 0% | 0% | 0% | Partial Internal |
| Vienna Insurance Group AG | Austria | 2020 | 2 | 238% | 7% | 0% | 43% | 0% | Partial Internal |
| Ageas SA | Belgium | 2016 | 2 | 174% | 17% | 0% | 8% | 0% | Partial Internal |
| Ageas SA | Belgium | 2017 | 2 | 191% | 4% | 0% | 9% | 0% | Partial Internal |
| Ageas SA | Belgium | 2018 | 2 | 216% | 40% | 0% | 11% | 0% | Partial Internal |
| Ageas SA | Belgium | 2019 | 2 | 203% | 11% | 0% | 9% | 0% | Partial Internal |
| Ageas SA | Belgium | 2020 | 2 | 199% | 13% | 0% | 9% | 0% | Partial Internal |
| KBC Groep NV | Belgium | 2016 | 1 | 203% | 12% | 0% | 0% | 0% | Standard Formula |
| KBC Groep NV | Belgium | 2017 | 1 | 212% | 2% | 0% | 0% | 0% | Standard Formula |
| KBC Groep NV | Belgium | 2018 | 1 | 217% | 20% | 0% | 0% | 0% | Standard Formula |
| KBC Groep NV | Belgium | 2019 | 1 | 202% | 5% | 0% | 0% | 0% | Standard Formula |
| KBC Groep NV | Belgium | 2020 | 1 | 222% | 6% | 0% | 0% | 0% | Standard Formula |
| Alm Brand A/S | Denmark | 2016 | 1 | 374% | 15% | 0% | 0% | 0% | Partial Internal |
| Alm Brand A/S | Denmark | 2017 | 1 | 285% | 7% | 0% | 0% | 0% | Partial Internal |
| Alm Brand A/S | Denmark | 2018 | 1 | 305% | 11% | 0% | 0% | 0% | Partial Internal |
| Alm Brand A/S | Denmark | 2019 | 1 | 316% | 5% | 0% | 0% | 0% | Partial Internal |
| Alm Brand A/S | Denmark | 2020 | 1 | 305% | 6% | 0% | 0% | 0% | Partial Internal |
| Topdanmark A/S | Denmark | 2016 | 1 | 174% | 31% | 0% | 0% | 0% | Partial Internal |
| Topdanmark A/S | Denmark | 2017 | 1 | 204% | 31% | 0% | 0% | 0% | Partial Internal |
| Topdanmark A/S | Denmark | 2018 | 1 | 196% | 41% | 0% | 0% | 0% | Partial Internal |
| Topdanmark A/S | Denmark | 2019 | 1 | 177% | 17% | 0% | 0% | 0% | Partial Internal |
| Topdanmark A/S | Denmark | 2020 | 1 | 170% | 18% | 0% | 0% | 0% | Partial Internal |
| Tryg A/S | Denmark | 2016 | 0 | 194% | 0% | 0% | 0% | 0% | Partial Internal |
| Tryg A/S | Denmark | 2017 | 0 | 281% | 0% | 0% | 0% | 0% | Partial Internal |
| Tryg A/S | Denmark | 2018 | 0 | 165% | 0% | 0% | 0% | 0% | Partial Internal |
| Tryg A/S | Denmark | 2019 | 0 | 162% | 0% | 0% | 0% | 0% | Partial Internal |
| Tryg A/S | Denmark | 2020 | 0 | 183% | 0% | 0% | 0% | 0% | Partial Internal |
| Sampo Plc | Finland | 2016 | 2 | 155% | 1% | 0% | 6% | 0% | Standard Formula |
| Sampo Plc | Finland | 2017 | 2 | 156% | 2% | 0% | 6% | 0% | Standard Formula |
| Sampo Plc | Finland | 2018 | 2 | 140% | 3% | 0% | 5% | 0% | Standard Formula |
| Sampo Plc | Finland | 2019 | 2 | 174% | 2% | 0% | 6% | 0% | Standard Formula |
| Sampo Plc | Finland | 2020 | 2 | 176% | 2% | 0% | 6% | 0% | Standard Formula |
| Axa SA | France | 2016 | 1 | 197% | 39% | 0% | 0% | 0% | Partial Internal |
| Axa SA | France | 2017 | 1 | 205% | 40% | 0% | 0% | 0% | Partial Internal |
| Axa SA | France | 2018 | 1 | 193% | 40% | 0% | 0% | 0% | Partial Internal |
| Axa SA | France | 2019 | 1 | 198% | 43% | 0% | 0% | 0% | Partial Internal |
| Axa SA | France | 2020 | 1 | 200% | 61% | 0% | 0% | 0% | Partial Internal |
| CNP Assurances SA | France | 2016 | 1 | 177% | 11% | 0% | 0% | 0% | Standard Formula |
| CNP Assurances SA | France | 2017 | 1 | 190% | 3% | 0% | 0% | 0% | Standard Formula |
| CNP Assurances SA | France | 2018 | 1 | 187% | 21% | 0% | 0% | 0% | Standard Formula |
| CNP Assurances SA | France | 2019 | 1 | 227% | 8% | 0% | 0% | 0% | Standard Formula |
| CNP Assurances SA | France | 2020 | 1 | 208% | 9% | 0% | 0% | 0% | Standard Formula |

| Firm name | Country | Year | LTGs Used | Solvency Reported | VA Impact | MA Impact | TP Impact | IR Impact | Model for SCR calculation |
|---|---|---|---|---|---|---|---|---|---|
| Coface SA | France | 2016 | 0 | 150% | 0% | 0% | 0% | 0% | Standard Formula |
| Coface SA | France | 2017 | 0 | 153% | 0% | 0% | 0% | 0% | Standard Formula |
| Coface SA | France | 2018 | 0 | 172% | 0% | 0% | 0% | 0% | Standard Formula |
| Coface SA | France | 2019 | 0 | 203% | 0% | 0% | 0% | 0% | Partial Internal |
| Coface SA | France | 2020 | 0 | 204% | 0% | 0% | 0% | 0% | Partial Internal |
| Scor SE | France | 2016 | 0 | 225% | 0% | 0% | 0% | 0% | Full Internal |
| Scor SE | France | 2017 | 0 | 213% | 0% | 0% | 0% | 0% | Full Internal |
| Scor SE | France | 2018 | 0 | 215% | 0% | 0% | 0% | 0% | Full Internal |
| Scor SE | France | 2019 | 0 | 226% | 0% | 0% | 0% | 0% | Full Internal |
| Scor SE | France | 2020 | 0 | 220% | 0% | 0% | 0% | 0% | Full Internal |
| Allianz SE | Germany | 2016 | 1 | 218% | 21% | 0% | 0% | 0% | Partial Internal |
| Allianz SE | Germany | 2017 | 1 | 229% | 18% | 0% | 0% | 0% | Partial Internal |
| Allianz SE | Germany | 2018 | 1 | 229% | 28% | 0% | 0% | 0% | Partial Internal |
| Allianz SE | Germany | 2019 | 1 | 212% | 25% | 0% | 0% | 0% | Partial Internal |
| Allianz SE | Germany | 2020 | 2 | 240% | 40% | 0% | 33% | 0% | Partial Internal |
| Muenchener Rueck AG | Germany | 2016 | 1 | 316% | 0% | 0% | 49% | 0% | Full Internal |
| Muenchener Rueck AG | Germany | 2017 | 2 | 297% | 0% | 0% | 53% | 0% | Full Internal |
| Muenchener Rueck AG | Germany | 2018 | 2 | 295% | 1% | 0% | 49% | 0% | Full Internal |
| Muenchener Rueck AG | Germany | 2019 | 2 | 274% | 5% | 0% | 39% | 0% | Full Internal |
| Muenchener Rueck AG | Germany | 2020 | 2 | 240% | 3% | 0% | 32% | 0% | Full Internal |
| Nürnberger Beteiligungs AG | Germany | 2016 | 1 | 262% | 0% | 0% | 113% | 0% | Standard Formula |
| Nürnberger Beteiligungs AG | Germany | 2017 | 1 | 341% | 0% | 0% | 100% | 0% | Standard Formula |
| Nürnberger Beteiligungs AG | Germany | 2018 | 1 | 283% | 0% | 0% | 77% | 0% | Standard Formula |
| Nürnberger Beteiligungs AG | Germany | 2019 | 1 | 286% | 0% | 0% | 62% | 0% | Standard Formula |
| Nürnberger Beteiligungs AG | Germany | 2020 | 1 | 270% | 0% | 0% | 56% | 0% | Standard Formula |
| Rheinland Holding AG | Germany | 2016 | 2 | 244% | 9% | 0% | 66% | 0% | Standard Formula |
| Rheinland Holding AG | Germany | 2017 | 2 | 260% | 3% | 0% | 69% | 0% | Standard Formula |
| Rheinland Holding AG | Germany | 2018 | 2 | 234% | 14% | 0% | 58% | 0% | Standard Formula |
| Rheinland Holding AG | Germany | 2019 | 2 | 217% | 4% | 0% | 38% | 0% | Standard Formula |
| Rheinland Holding AG | Germany | 2020 | 2 | 287% | 12% | 0% | 0% | 48% | Standard Formula |
| Talanx AG | Germany | 2016 | 2 | 236% | 49% | 0% | 50% | 0% | Partial Internal |
| Talanx AG | Germany | 2017 | 2 | 253% | 41% | 0% | 47% | 0% | Partial Internal |
| Talanx AG | Germany | 2018 | 2 | 252% | 35% | 0% | 43% | 0% | Partial Internal |
| Talanx AG | Germany | 2019 | 2 | 246% | 54% | 0% | 36% | 0% | Full Internal |
| Talanx AG | Germany | 2020 | 2 | 260% | 60% | 0% | 54% | 0% | Full Internal |
| Wuestenrot & Wuerttem. AG | Germany | 2016 | 2 | 194% | 7% | 0% | 52% | 0% | Standard Formula |
| Wuestenrot & Wuerttem. AG | Germany | 2017 | 2 | 201% | 1% | 0% | 47% | 0% | Standard Formula |
| Wuestenrot & Wuerttem. AG | Germany | 2018 | 2 | 255% | 29% | 0% | 65% | 0% | Standard Formula |
| Wuestenrot & Wuerttem. AG | Germany | 2019 | 2 | 238% | 8% | 0% | 55% | 0% | Standard Formula |
| Wuestenrot & Wuerttem. AG | Germany | 2020 | 2 | 233% | 10% | 0% | 48% | 0% | Standard Formula |
| European Reliance Gen. Ins. | Greece | 2016 | 1 | 125% | 2% | 0% | 0% | 0% | Standard Formula |
| European Reliance Gen. Ins. | Greece | 2017 | 1 | 146% | 1% | 0% | 0% | 0% | Standard Formula |
| European Reliance Gen. Ins. | Greece | 2018 | 1 | 160% | 4% | 0% | 0% | 0% | Standard Formula |
| European Reliance Gen. Ins. | Greece | 2019 | 1 | 168% | 1% | 0% | 0% | 0% | Standard Formula |
| European Reliance Gen. Ins. | Greece | 2020 | 1 | 175% | 1% | 0% | 0% | 0% | Standard Formula |
| FBD Holdings Plc | Ireland | 2016 | 0 | 126% | 0% | 0% | 0% | 0% | Standard Formula |
| FBD Holdings Plc | Ireland | 2017 | 0 | 164% | 0% | 0% | 0% | 0% | Standard Formula |
| FBD Holdings Plc | Ireland | 2018 | 0 | 165% | 0% | 0% | 0% | 0% | Standard Formula |
| FBD Holdings Plc | Ireland | 2019 | 0 | 193% | 0% | 0% | 0% | 0% | Standard Formula |
| FBD Holdings Plc | Ireland | 2020 | 0 | 197% | 0% | 0% | 0% | 0% | Standard Formula |
| Assicurazioni Generali SpA | Italy | 2016 | 1 | 178% | 45% | 0% | 0% | 0% | Partial Internal |
| Assicurazioni Generali SpA | Italy | 2017 | 1 | 207% | 42% | 0% | 0% | 0% | Partial Internal |
| Assicurazioni Generali SpA | Italy | 2018 | 1 | 217% | 66% | 0% | 0% | 0% | Partial Internal |
| Assicurazioni Generali SpA | Italy | 2019 | 1 | 224% | 59% | 0% | 0% | 0% | Partial Internal |
| Assicurazioni Generali SpA | Italy | 2020 | 2 | 224% | 68% | 0% | 1% | 0% | Partial Internal |

| Firm name | Country | Year | LTGs Used | Solvency Reported | VA Impact | MA Impact | TP Impact | IR Impact | Model for SCR calculation |
|---|---|---|---|---|---|---|---|---|---|
| Societa Cattolica di Assic. Sc | Italy | 2016 | 1 | 186% | 13% | 0% | 0% | 0% | Standard Formula |
| Societa Cattolica di Assic. Sc | Italy | 2017 | 1 | 239% | 3% | 0% | 0% | 0% | Standard Formula |
| Societa Cattolica di Assic. Sc | Italy | 2018 | 1 | 171% | 21% | 0% | 0% | 0% | Standard Formula |
| Societa Cattolica di Assic. Sc | Italy | 2019 | 1 | 175% | 7% | 0% | 0% | 0% | Standard Formula |
| Societa Cattolica di Assic. Sc | Italy | 2020 | 1 | 187% | 8% | 0% | 0% | 0% | Standard Formula |
| UnipolSai Assicurazioni SpA | Italy | 2016 | 1 | 243% | 8% | 0% | 0% | 0% | Partial Internal |
| UnipolSai Assicurazioni SpA | Italy | 2017 | 1 | 263% | 2% | 0% | 0% | 0% | Partial Internal |
| UnipolSai Assicurazioni SpA | Italy | 2018 | 1 | 253% | 27% | 0% | 0% | 0% | Partial Internal |
| UnipolSai Assicurazioni SpA | Italy | 2019 | 1 | 284% | 5% | 0% | 0% | 0% | Partial Internal |
| UnipolSai Assicurazioni SpA | Italy | 2020 | 1 | 318% | 3% | 0% | 0% | 0% | Partial Internal |
| Vittoria Assicurazioni SpA | Italy | 2016 | 1 | 219% | 4% | 0% | 0% | 0% | Standard Formula |
| Vittoria Assicurazioni SpA | Italy | 2017 | 1 | 216% | 2% | 0% | 0% | 0% | Standard Formula |
| Vittoria Assicurazioni SpA | Italy | 2018 | 1 | 257% | 11% | 0% | 0% | 0% | Standard Formula |
| Vittoria Assicurazioni SpA | Italy | 2019 | 1 | 257% | 1% | 0% | 0% | 0% | Standard Formula |
| Vittoria Assicurazioni SpA | Italy | 2020 | 1 | 194% | 2% | 0% | 0% | 0% | Standard Formula |
| Aegon NV | Netherl. | 2016 | 3 | 157% | 24% | 2% | 1% | 0% | Partial Internal |
| Aegon NV | Netherl. | 2017 | 3 | 201% | 31% | 2% | 1% | 0% | Partial Internal |
| Aegon NV | Netherl. | 2018 | 3 | 211% | 35% | 2% | 1% | 0% | Partial Internal |
| Aegon NV | Netherl. | 2019 | 2 | 201% | 22% | 2% | 0% | 0% | Partial Internal |
| Aegon NV | Netherl. | 2020 | 2 | 196% | 30% | 2% | 0% | 0% | Partial Internal |
| ASR Nederland NV | Netherl. | 2016 | 1 | 189% | 14% | 0% | 0% | 0% | Standard Formula |
| ASR Nederland NV | Netherl. | 2017 | 1 | 195% | 1% | 0% | 0% | 0% | Standard Formula |
| ASR Nederland NV | Netherl. | 2018 | 1 | 195% | 27% | 0% | 0% | 0% | Standard Formula |
| ASR Nederland NV | Netherl. | 2019 | 1 | 193% | 8% | 0% | 0% | 0% | Standard Formula |
| ASR Nederland NV | Netherl. | 2020 | 1 | 199% | 8% | 0% | 0% | 0% | Standard Formula |
| Delta Lloyd NV | Netherl. | 2016 | 1 | 143% | 33% | 0% | 0% | 0% | Standard Formula |
| NN Group NV | Netherl. | 2016 | 3 | 241% | 122% | 0% | 3% | 1% | Partial Internal |
| NN Group NV | Netherl. | 2017 | 3 | 199% | 75% | 0% | 1% | 1% | Partial Internal |
| NN Group NV | Netherl. | 2018 | 3 | 230% | 128% | 0% | 3% | 1% | Partial Internal |
| NN Group NV | Netherl. | 2019 | 3 | 218% | 97% | 0% | 5% | 1% | Partial Internal |
| NN Group NV | Netherl. | 2020 | 3 | 210% | 98% | 0% | 4% | 1% | Partial Internal |
| Gjensidige Forsikring ASA | Norway | 2016 | 0 | 147% | 0% | 0% | 0% | 0% | Standard Formula |
| Gjensidige Forsikring ASA | Norway | 2017 | 0 | 137% | 0% | 0% | 0% | 0% | Standard Formula |
| Gjensidige Forsikring ASA | Norway | 2018 | 0 | 169% | 0% | 0% | 0% | 0% | Partial Internal |
| Gjensidige Forsikring ASA | Norway | 2019 | 0 | 231% | 0% | 0% | 0% | 0% | Partial Internal |
| Gjensidige Forsikring ASA | Norway | 2020 | 0 | 199% | 0% | 0% | 0% | 0% | Partial Internal |
| Protector Forsikring ASA | Norway | 2016 | 0 | 163% | 0% | 0% | 0% | 0% | Standard Formula |
| Protector Forsikring ASA | Norway | 2017 | 0 | 201% | 0% | 0% | 0% | 0% | Standard Formula |
| Protector Forsikring ASA | Norway | 2018 | 0 | 175% | 0% | 0% | 0% | 0% | Standard Formula |
| Protector Forsikring ASA | Norway | 2019 | 0 | 168% | 0% | 0% | 0% | 0% | Standard Formula |
| Protector Forsikring ASA | Norway | 2020 | 1 | 190% | 4% | 0% | 0% | 0% | Standard Formula |
| Storebrand ASA | Norway | 2016 | 2 | 157% | 16% | 0% | 9% | 0% | Standard Formula |
| Storebrand ASA | Norway | 2017 | 2 | 172% | 10% | 0% | 13% | 0% | Standard Formula |
| Storebrand ASA | Norway | 2018 | 1 | 173% | 21% | 0% | 0% | 0% | Standard Formula |
| Storebrand ASA | Norway | 2019 | 1 | 187% | 21% | 0% | 0% | 0% | Standard Formula |
| Storebrand ASA | Norway | 2020 | 2 | 178% | 17% | 0% | 12% | 0% | Standard Formula |
| Powszechny Zaklad Ubez. SA | Poland | 2016 | 0 | 250% | 0% | 0% | 0% | 0% | Standard Formula |
| Powszechny Zaklad Ubez. SA | Poland | 2017 | 0 | 208% | 0% | 0% | 0% | 0% | Standard Formula |
| Powszechny Zaklad Ubez. SA | Poland | 2018 | 0 | 222% | 0% | 0% | 0% | 0% | Standard Formula |
| Powszechny Zaklad Ubez. SA | Poland | 2019 | 0 | 245% | 0% | 0% | 0% | 0% | Standard Formula |
| Powszechny Zaklad Ubez. SA | Poland | 2020 | 0 | 236% | 0% | 0% | 0% | 0% | Standard Formula |
| Pozavarovalnica Sava dd | Slovenia | 2016 | 0 | 204% | 0% | 0% | 0% | 0% | Standard Formula |
| Pozavarovalnica Sava dd | Slovenia | 2017 | 0 | 216% | 0% | 0% | 0% | 0% | Standard Formula |
| Pozavarovalnica Sava dd | Slovenia | 2018 | 0 | 218% | 0% | 0% | 0% | 0% | Standard Formula |
| Pozavarovalnica Sava dd | Slovenia | 2019 | 0 | 220% | 0% | 0% | 0% | 0% | Standard Formula |
| Pozavarovalnica Sava dd | Slovenia | 2020 | 0 | 198% | 0% | 0% | 0% | 0% | Standard Formula |

| Firm name | Country | Year | LTGs Used | Solvency Reported | VA Impact | MA Impact | TP Impact | IR Impact | Model for SCR calculation |
|---|---|---|---|---|---|---|---|---|---|
| Zavarovalnica Triglav dd | Slovenia | 2016 | 0 | 246% | 0% | 0% | 0% | 0% | Standard Formula |
| Zavarovalnica Triglav dd | Slovenia | 2017 | 0 | 222% | 0% | 0% | 0% | 0% | Standard Formula |
| Zavarovalnica Triglav dd | Slovenia | 2018 | 0 | 216% | 0% | 0% | 0% | 0% | Standard Formula |
| Zavarovalnica Triglav dd | Slovenia | 2019 | 0 | 223% | 0% | 0% | 0% | 0% | Standard Formula |
| Zavarovalnica Triglav dd | Slovenia | 2020 | 0 | 240% | 0% | 0% | 0% | 0% | Standard Formula |
| Grupo Catalana Occidente SA | Spain | 2016 | 2 | 200% | 1% | 0% | 16% | 0% | Standard Formula |
| Grupo Catalana Occidente SA | Spain | 2017 | 2 | 210% | 0% | 0% | 2% | 0% | Partial Internal |
| Grupo Catalana Occidente SA | Spain | 2018 | 1 | 207% | 2% | 0% | 0% | 0% | Partial Internal |
| Grupo Catalana Occidente SA | Spain | 2019 | 2 | 213% | 1% | 0% | 10% | 0% | Partial Internal |
| Grupo Catalana Occidente SA | Spain | 2020 | 2 | 216% | 1% | 0% | 10% | 0% | Partial Internal |
| Mapfre SA | Spain | 2016 | 3 | 210% | 2% | 3% | 18% | 0% | Standard Formula |
| Mapfre SA | Spain | 2017 | 3 | 200% | 0% | 3% | 17% | 0% | Standard Formula |
| Mapfre SA | Spain | 2018 | 3 | 190% | 3% | 3% | 15% | 0% | Standard Formula |
| Mapfre SA | Spain | 2019 | 3 | 187% | 1% | -6% | 14% | 0% | Standard Formula |
| Mapfre SA | Spain | 2020 | 3 | 193% | 1% | -1% | 14% | 0% | Partial Internal |
| Admiral Group PLC | UK | 2016 | 0 | 183% | 0% | 0% | 0% | 0% | Standard Formula |
| Admiral Group PLC | UK | 2017 | 1 | 193% | 3% | 0% | 0% | 0% | Standard Formula |
| Admiral Group PLC | UK | 2018 | 1 | 170% | 5% | 0% | 0% | 0% | Standard Formula |
| Admiral Group PLC | UK | 2019 | 1 | 170% | 5% | 0% | 0% | 0% | Standard Formula |
| Admiral Group PLC | UK | 2020 | 1 | 209% | 1% | 0% | 0% | 0% | Standard Formula |
| Aviva PLC | UK | 2016 | 3 | 172% | 6% | 90% | 33% | 0% | Partial Internal |
| Aviva PLC | UK | 2017 | 3 | 169% | 3% | 74% | 31% | 0% | Partial Internal |
| Aviva PLC | UK | 2018 | 3 | 180% | 14% | 82% | 31% | 0% | Partial Internal |
| Aviva PLC | UK | 2019 | 3 | 183% | 13% | 85% | 29% | 0% | Partial Internal |
| Aviva PLC | UK | 2020 | 3 | 178% | 22% | 85% | 27% | 0% | Partial Internal |
| Beazley PLC | UK | 2016 | 0 | 237% | 0% | 0% | 0% | 0% | Full Internal |
| Beazley PLC | UK | 2017 | 0 | 223% | 0% | 0% | 0% | 0% | Full Internal |
| Beazley PLC | UK | 2018 | 0 | 202% | 0% | 0% | 0% | 0% | Full Internal |
| Beazley PLC | UK | 2019 | 0 | 151% | 0% | 0% | 0% | 0% | Full Internal |
| Beazley PLC | UK | 2020 | 0 | 159% | 0% | 0% | 0% | 0% | Full Internal |
| Chesnara PLC | UK | 2016 | 0 | 158% | 0% | 0% | 0% | 0% | Standard Formula |
| Chesnara PLC | UK | 2017 | 0 | 146% | 0% | 0% | 0% | 0% | Standard Formula |
| Chesnara PLC | UK | 2018 | 0 | 158% | 0% | 0% | 0% | 0% | Standard Formula |
| Chesnara PLC | UK | 2019 | 0 | 155% | 0% | 0% | 0% | 0% | Standard Formula |
| Chesnara PLC | UK | 2020 | 1 | 156% | 2% | 0% | 0% | 0% | Standard Formula |
| Direct Line Insurance Group | UK | 2016 | 1 | 165% | 3% | 0% | 0% | 0% | Partial Internal |
| Direct Line Insurance Group | UK | 2017 | 1 | 165% | 2% | 0% | 0% | 0% | Partial Internal |
| Direct Line Insurance Group | UK | 2018 | 1 | 170% | 3% | 0% | 0% | 0% | Partial Internal |
| Direct Line Insurance Group | UK | 2019 | 1 | 165% | 1% | 0% | 0% | 0% | Partial Internal |
| Direct Line Insurance Group | UK | 2020 | 1 | 191% | 1% | 0% | 0% | 0% | Partial Internal |
| Hansard Global PLC | UK | 2016 | 0 | 246% | 0% | 0% | 0% | 0% | Standard Formula |
| Hansard Global PLC | UK | 2017 | 0 | 249% | 0% | 0% | 0% | 0% | Standard Formula |
| Hansard Global PLC | UK | 2018 | 0 | 242% | 0% | 0% | 0% | 0% | Standard Formula |
| Hansard Global PLC | UK | 2019 | 0 | 243% | 0% | 0% | 0% | 0% | Standard Formula |
| Hansard Global PLC | UK | 2020 | 0 | 187% | 0% | 0% | 0% | 0% | Standard Formula |
| Legal & General Group PLC | UK | 2016 | 2 | 163% | 0% | 124% | 75% | 0% | Partial Internal |
| Legal & General Group PLC | UK | 2017 | 2 | 181% | 0% | 137% | 72% | 0% | Partial Internal |
| Legal & General Group PLC | UK | 2018 | 2 | 189% | 0% | 165% | 71% | 0% | Partial Internal |
| Legal & General Group PLC | UK | 2019 | 2 | 179% | 0% | 157% | 60% | 0% | Partial Internal |
| Legal & General Group PLC | UK | 2020 | 2 | 175% | 0% | 159% | 56% | 0% | Partial Internal |
| Old Mutual PLC | UK | 2016 | 0 | 122% | 0% | 0% | 0% | 0% | Standard Formula |
| Old Mutual PLC | UK | 2017 | 0 | 123% | 0% | 0% | 0% | 0% | Standard Formula |
| Phoenix Group Holdings | UK | 2016 | 2 | 140% | 0% | 36% | 47% | 0% | Partial Internal |
| Phoenix Group Holdings | UK | 2017 | 2 | 138% | 0% | 34% | 39% | 0% | Partial Internal |
| Phoenix Group Holdings | UK | 2018 | 3 | 146% | 0% | 42% | 38% | 0% | Partial Internal |
| Phoenix Group Holdings | UK | 2019 | 3 | 140% | 0% | 41% | 40% | 0% | Partial Internal |
| Phoenix Group Holdings | UK | 2020 | 3 | 145% | 1% | 50% | 33% | 0% | Partial Internal |

| Firm name | Country | Year | LTGs Used | Solvency Reported | VA Impact | MA Impact | TP Impact | IR Impact | Model for SCR calculation |
|---|---|---|---|---|---|---|---|---|---|
| Prudential PLC | UK | 2016 | 3 | 171% | 3% | 53% | 17% | 0% | Partial Internal |
| Prudential PLC | UK | 2017 | 3 | 168% | 2% | 45% | 13% | 0% | Partial Internal |
| Prudential PLC | UK | 2018 | 3 | 192% | 8% | 38% | 10% | 0% | Partial Internal |
| RSA Insurance Group PLC | UK | 2016 | 0 | 158% | 0% | 0% | 0% | 0% | Full Internal |
| RSA Insurance Group PLC | UK | 2017 | 0 | 163% | 0% | 0% | 0% | 0% | Full Internal |
| RSA Insurance Group PLC | UK | 2018 | 0 | 170% | 0% | 0% | 0% | 0% | Full Internal |
| RSA Insurance Group PLC | UK | 2019 | 0 | 178% | 0% | 0% | 0% | 0% | Full Internal |
| RSA Insurance Group PLC | UK | 2020 | 0 | 189% | 0% | 0% | 0% | 0% | Full Internal |
| St. James's Place PLC | UK | 2016 | 0 | 141% | 0% | 0% | 0% | 0% | Standard Formula |
| St. James's Place PLC | UK | 2017 | 0 | 133% | 0% | 0% | 0% | 0% | Standard Formula |
| St. James's Place PLC | UK | 2018 | 0 | 137% | 0% | 0% | 0% | 0% | Standard Formula |
| St. James's Place PLC | UK | 2019 | 0 | 126% | 0% | 0% | 0% | 0% | Standard Formula |
| St. James's Place PLC | UK | 2020 | 0 | 124% | 0% | 0% | 0% | 0% | Standard Formula |
| Standard Life Aberdeen PLC | UK | 2016 | 3 | 177% | 2% | 32% | 36% | 0% | Partial Internal |
| Standard Life Aberdeen PLC | UK | 2017 | 3 | 185% | 1% | 34% | 24% | 0% | Partial Internal |

*Table A4: Solvency II data on insurer level (displayed on five pages)*

# IV. Robustness

| Variable of interest | Robustness check | Initial results | | | 1. T-values | | | 2. 5-year time windows | | | 3. Weighted CDS | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Dep. var. | VA | MA | TP | VA | MA | TP | VA | MA | TP | VA | MA | TP |
| Solvency pre LTG $k_{i,y}$ | | ✓*** | ✓' | ✓*** | ✓*** | ✓* | ✓*** | ✓*** | ✓ | ✓*** | ✓*** | ✓' | ✓*** |
| Sensitivity y10$_{i,y}$ | | ✓*** | - | ✓* | ✓*** | - | ✓* | ✓* | - | ✓*** | ✓*** | - | ✓* |
| Sensitivity CDS$_{i,y}$ | | - | ✓*** | - | - | ✓*** | - | ✓* | ✓* | - | - | ✓** | - |
| Sensitivity Index$_{i,y}$ | | - | - | - | - | - | - | - | - | - | - | - | - |
| ln(Size)$_{i,y}$ | | ✓' | ✓*** | ✓' | ✓ | ✓*** | ✓' | ✓' | ✓*** | ✓* | ✓' | ✓*** | ✓' |
| Life Share$_{i,y}$ | | ✓** | - | - | ✓** | - | - | ✓* | - | - | ✓* | - | - |

| Variable of interest | Robustness check | 4. National stock index | | | 5. Winsorizing in stage one | | | 6. Winsorizing in stage two | | | 7. With micro-cap insurers | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Dep. var. | VA | MA | TP | VA | MA | TP | VA | MA | TP | VA | MA | TP |
| Solvency pre LTG $k_{i,y}$ | | ✓*** | ✓' | ✓*** | ✓*** | ✓' | ✓*** | ✓*** | ✓' | ✓*** | ✓*** | ✓' | ✓*** |
| Sensitivity y10$_{i,y}$ | | ✓* | - | ✓' | ✓*** | - | ✓** | ✓*** | - | ✓* | ✓* | - | ✓ |
| Sensitivity CDS$_{i,y}$ | | - | ✓*** | - | - | ✓* | - | - | ✓*** | - | - | ✓** | - |
| Sensitivity Index$_{i,y}$ | | - | - | - | - | - | - | - | - | - | - | - | - |
| ln(Size)$_{i,y}$ | | ✓* | ✓*** | ✓' | ✓* | ✓*** | ✓' | ✓* | ✓*** | ✓ | ✓** | ✓*** | ✓ |
| Life Share$_{i,y}$ | | ✓* | - | - | ✓* | - | - | ✓** | - | - | ✓** | - | - |

Note: Each robustness test represents an adjustment to our empirical models from Equations (8) to (10). ***, **, *, ' indicate significance at the 1%, 5%, 10%, and 15% levels, respectively. The check symbol indicates that, under the given specification, the coefficient on the variable of interest from the panel regression analysis has a sign that is consistent with the initial results.

*Table A5: Overview of regression results for robustness tests[31]*

[31] The full regression tables including all coefficients, p-values and regression statistics are available upon request.

# V. Additional results

| Dependent variable: | Internal Market Risk$_{i,y}$ (1) | Internal Spread Risk$_{i,y}$ (2) | Internal Default Risk$_{i,y}$ (3) | EU Gov Bond Default Risk$_{i,y}$ (4) |
|---|---|---|---|---|
| Solv. pre LTG1$_{i,y}$ | 1.397 | 2.282 | 0.315 | 8.454 |
| | (0.514) | (0.476) | (0.897) | (0.107) |
| Sensitivity y10$_{i,y}$ | 11.449 | 13.134 | 12.231* | 20.179 |
| | (0.188) | (0.154) | (0.080) | (0.219) |
| Sensitivity CDS$_{i,y}$ | 181.462*** | 153.719*** | 80.072 | 60.044 |
| | (0.001) | (0.000) | (0.123) | (0.517) |
| Sensitivity Index$_{i,y}$ | 22.303** | 20.970*** | -4.631 | -8.559 |
| | (0.014) | (0.003) | (0.301) | (0.464) |
| ln(Size$_{i,y}$) | 8.432*** | 6.668*** | 8.018*** | 12.581*** |
| | (0.000) | (0.003) | (0.000) | (0.001) |
| Life Share$_{i,y}$ | 2.132 | -4.415 | -21.044*** | -2.839 |
| | (0.741) | (0.504) | (0.000) | (0.887) |
| No. of obs. | 225 | 225 | 225 | 225 |
| No. of insurers | 47 | 47 | 47 | 47 |
| Wald chi$^2$ | 96.273 | 40.846 | 48.139 | 22.671 |
| Log likelihood | -31.285 | -31.595 | -21.892 | -8.867 |
| Sigma | 19.797 | 15.764 | 12.232 | 14.050 |
| Rho | 0.992 | 0.987 | 0.978 | 0.984 |

Note: Logarithmic regressions of insurers' annual use of internal models from 2016 to 2020 with random effects. Sources: SFCRs (qualitative information on internal models from Section E.4 and solvency ratio from QRT S.22.01.22), SNL (insurer-level size and share of life insurance reserves). Market risk sensitivity coefficients (betas) are estimated in the first stage of the regression analyses. ***, **, * indicate significance at the 1%, 5% and 10% levels respectively. P-values are shown in parentheses.

*Table A6: Determinants of internal models*

# Literature

Asadi, S., Al Janabi, M. A. M. (2020), 'Measuring market and credit risk under Solvency II: evaluation of the standard technique versus internal models for stock and bond markets', *European Actuarial Journal*, 10: 425–456.

BaFin (2020), '2020 Annual Report - Federal Financial Supervisory Authority', Bundesanstalt für Finanzdienstleistungsaufsicht, https://www.bafin.de/EN/PublikationenDaten/Jahresbericht/jahresbericht_node_en.html.

Berends, K., McMenamin, R., Plestis, T., Rosen, R. (2013), 'The sensitivity of life insurance firms to interest rate changes', *Federal Reserve Bank of Chicago Economic Perspectives*, 37 (2): 47-78.

Braun, A., Schmeiser, H., Schreiber, F. (2017). 'Portfolio optimization under Solvency II: Implicit constraints imposed by the market risk standard formula', *Journal of Risk and Insurance*, 84 (1): 177-207.

Brechmann, E. C., Czado, C. (2013), 'Risk management with high-dimensional vine copulas: An analysis of the Euro Stoxx 50', *Statistics & Risk Modeling*, 30 (4): 307-342.

Brewer, E., Carson, J. M., Elyasiani, E., Mansur, I., Scott, W. L. (2007), 'Interest rate risk and equity values of life insurance companies: A GARCH-M model', *Journal of Risk and Insurance*, 74 (2): 401-423.

Campbell, J. Y., Lettau, M., Malkiel, B. G., Xu, Y. (2001), 'Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk', *The Journal of Finance*, 56 (1): 1-43.

Carson, J. M., Elyasiani, E., Mansur, I. (2008), 'Market risk, interest rate risk, and inter-dependencies in insurer stock returns: A System-GARCH model', Journal of Risk and Insurance, 75 (4): 873-891.

Chaplin, R. A., Stirling, R. W., Belcher, G. D. (2022), 'From Solvency II to Solvency UK: The UK Government Announces Its Post-Brexit Solvency II Reforms', Skadden, Arps, Slate, Meagher & Flom LLP, https://www.skadden.com/insights/publications/2022/11/from-solvency-ii-to-solvency-uk.

Colliard, J.-E. (2019), ‘Strategic Selection of Risk Models and Bank Capital Regulation’, *Management Science*, 65 (6): 2591-2606.

Crean, A., Foroughi, K. (2017), ‘Solvency II one year on: One step forward, two steps back’, Willis Towers Watson / Autonomous, https://www.wtwco.com/-/media/wtw/insights/2017/04/solvency-ii-one-year-on.pdf.

Da, Z., Guo, R. J., & Jagannathan, R. (2012), ‘CAPM for estimating the cost of equity capital: Interpreting the empirical evidence’, *Journal of Financial Economics*, 103 (1): 204-220.

Düll, R., König, F., Ohls, J. (2017), ‘On the exposure of insurance companies to sovereign risk portfolio investments and market forces’, *Journal of Financial Stability*, 31: 93-106.

Duverne, D., Hele, J. (2017), ‘How the Insurance Industry Manages Risk’, in: Hufeld, F., Koijen, R. S. J., Thimann, C. (Eds.), The Economics, Regulation, and Systemic Risk of Insurance Markets, Oxford University Press, Oxford, Ch. 3: 55-75.

EIOPA (2014), ‘The underlying assumptions in the standard formula for the Solvency Capital Requirement calculation’, EIOPA-14-322, July 2014, https://www.bafin.de/SharedDocs/Downloads/EN/Leitfaden/VA/dl_lf_solvency_annahmen_standardformel_scr_en.html.

EIOPA (2016a), ‘2016 EIOPA Insurance Stress Test Report’, EIOPA 16/302, December 2016, https://www.eiopa.europa.eu/system/files/2019-09/eiopa-bos-16-302_insurance_stress_test_2016_report.pdf.

EIOPA (2016b), ‘Report on long-term guarantees measures and measures on equity risk 2016’, EIOPA-BoS-16/279, December 2016, https://register.eiopa.europa.eu/Publications/Responses/EIOPA-BoS-16-279_LTG_REPORT_2016.pdf.

EIOPA (2017a), ‘Investment behavior report’, EIOPA-BoS-17/230, November 2017, https://www.eiopa.europa.eu/system/files/2020-01/investment_behaviour_report.pdf.

EIOPA (2017b), ‘Report on long-term guarantees measures and measures on equity risk 2017’, EIOPA-BoS-17/334, December 2017, https://register.eiopa.europa.eu/Publications/Reports/2017-12-20%20LTG%20Report%202017.pdf.

EIOPA (2018), 'Report on long-term guarantees measures and measures on equity risk 2018', EIOPA-BoS-18/471, December 2018, https://register.eiopa.europa.eu/Publications/Reports/2018-12-18%20_LTG%20AnnualReport2018.pdf.

EIOPA (2020), 'Report on long-term guarantees measures and measures on equity risk 2020', EIOPA-BoS-20/706, December 2020, https://www.eiopa.europa.eu/system/files/2020-12/eiopa-bos-20-706-long-term-guarantees-ltg-report-2020.pdf.

EIOPA (2023), 'Insurance statistics', https://www.eiopa.europa.eu/tools-and-data/insurance-statistics_en.

European Commission (2009), 'Directive 2009/138/EC of the European Parliament and of the Council of 25 November 2009 on the taking-up and pursuit of the business of Insurance and Reinsurance (Solvency II)', *Official Journal of the European Union*, December 2009.

European Commission (2015), 'Commission Delegated Regulation (EU) 2015/35 of 10 October 2014 supplementing Directive 2009/138/EC of the European Parliament and of the Council on the taking-up and pursuit of the business of Insurance and Reinsurance (Solvency II)', *Official Journal of the European Union*, January 2015.

Fischer, K., Schlütter, S. (2015). 'Optimal investment strategies for insurance companies when capital requirements are imposed by a standard formula', *The Geneva Risk and Insurance Review*, 40, 15-40.

Frey, A. (2012) 'Facing the interest rate challenge', *Sigma Study*, No. 4/2012, Swiss Re, https://www.swissre.com/institute/research/sigma-research/sigma-2012-04.html.

Gatzert, N., Hedinger, D. (2020), 'An Empirical Analysis of Market Reactions to the First Solvency and Financial Condition Reports in the European Insurance Industry', *Journal of Risk and Insurance*, 87 (2): 407-436.

Grochola, N., Browne, M. J., Gründl, H., Schlütter, S. (2023), 'Exploring the market risk profiles of U.S. and European stock insurers', ICIR Working Paper Series No. 39/2021.

Hakenes, H., Schnabel, I. (2011), 'Bank size and risk-taking under Basel II', *Journal of Banking & Finance*, 35 (6): 1436-1449.

Hartley, D., Paulson, A., Rosen, R. J. (2017), 'Measuring Interest Rate Risk in the Life Insurance Sector: The U.S. and the U.K.', in: Hufeld, F., Koijen, R. S. J., Thimann, C. (Eds.), *The Economics, Regulation, and Systemic Risk of Insurance Markets*, Oxford University Press, Oxford, Ch. 6: 124-150.

Lins, K. V., Servaes, H., Tamayo, A. (2017), 'Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis', *The Journal of Finance*, 72(4): 1785-1824.

Möhlmann, A. (2021), 'Interest rate risk of life insurers – evidence from accounting data', *Financial Management*, 50 (2): 587-612.

Mukhtarov, S., Schoute, M., Wielhouwer, J. L. (2022), 'The information content of the Solvency II ratio relative to earnings', *Journal of Risk and Insurance*, 89(1): 237-266.

Plosser, M. C., Santos, J. A. C. (2014), 'Banks' Incentives and the Quality of Internal Risk Models', Staff Reports 704, Federal Reserve Bank of New York.

Thibeault, A., Wambeke, M. (2014), 'Regulatory impact on banks' and insurers' investments', Vlerick Business School Working Paper.

Wilson, T. C. (2013), 'Risk Management in the Face of Risky Sovereign Debt: Four Observations', *BIS Papers*, No. 72, 130-135.