Received: 27 April 2025 | Revised: 1 July 2025 | Accepted: 12 August 2025

DOI: 10.1111/jori.70019

ORIGINAL ARTICLE

Journal of Risk and Insurance

Market discipline in life insurance: Does public risk disclosure encourage less risky management actions?

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Abstract

We analyze how public risk disclosure, specifically Solvency II, impacts life insurers' risk-taking behavior. Using data from 58 German life insurers from 2016 to 2023, we find that publicly reported solvency ratios can affect premium growth and surrender rates. Moreover, insurers appear to improve their solvency ratios following a decline in the previous year. To investigate whether policyholder behavior drives a life insurer's reduced risk-taking, we then develop a model in which a life insurer seeks to maximize shareholder value. Unlike previous research, we consider *annually* disclosed solvency ratios, affecting policyholders' *dynamic* purchase and surrender behavior. In our model, the insurer acts less riskily (e.g., holds more reserves and sells less-risky insurance portfolios) to maintain higher solvency ratios and mitigate policyholders' adverse reactions. Our findings motivate public risk disclosure to strengthen market discipline, but its level and design must be carefully calibrated to be effective and avoid undue costs.

KEYWORDS
life insurance, market discipline, risk disclosure, shareholder value maximization

JEL CLASSIFICATION
G22, G32, G38

1 | INTRODUCTION

Market discipline refers to stakeholders' ability to monitor and influence a company's management (see Eling, 2012). In finance, it can serve as an internal force to encourage financial institutions to adopt less risky practices, complementing regulatory oversight (see Crockett, 2002; Flannery & Bliss, 2019). To strengthen market discipline in insurance, Solvency II mandates that European insurers publish an annual Solvency and Financial Condition Report (SFCR) to inform the public about their financial strength since 2016. Beyond investors, this transparency allows customers to discipline insurers through their purchase and surrender behavior. Customer-driven market discipline seems particularly relevant in life insurance, where higher premiums, longer contract terms, and group contracts increase reliance on financial advice.

While Gatzert and Heidinger (2020) observed stock market reactions to the first SFCR publication for the fiscal year 2016, customer reactions (e.g., changes in purchase and surrender behavior) have not been analyzed. Moreover, it remains unclear whether public risk disclosure, as mandated by Solvency II, genuinely encourages insurers to adopt less risky management practices, justifying the associated disclosure costs (see Eling, 2012; Rae et al., 2018). Therefore, we first provide empirical evidence that changes in life insurers' publicly reported solvency ratios under Solvency II influence premium growth, surrender rates, and reactive changes in solvency ratios in the subsequent year. We then use a shareholder value maximization model, calibrated on these empirical observations, to demonstrate that public risk disclosure can encourage less risky management practices. The effectiveness of this mechanism depends on the strength of policyholders' reactions and the premium loadings of products.

Our research builds on the substantial literature examining the monitoring dimension of market discipline in insurance (see Eling, 2012). Empirical research has shown that changes in the financial ratings of insurers impact stock prices (e.g., Halek & Eckles, 2010; Singh & Power, 1992), as well as premium growth and surrender rates (e.g., Castagnolo & Ferro, 2013; Deng et al., 2024; Eling & Schmit, 2012; Epermanis & Harrington, 2006; Phillips et al., 1998; Sommer, 1996). Stronger market reactions are generally observed for rating downgrades than upgrades (see Halek & Eckles, 2010) with the effects being more pronounced in life insurance than other lines of insurance (see Eling & Schmit, 2012). However, market reactions to publicly reported solvency ratios are rarely analyzed (see Gatzert & Heidinger, 2020; Park & Tokutsune, 2013). To the best of our knowledge, we are the first to investigate how changes in publicly reported solvency ratios mandated by Solvency II affect life insurers' premium growth, surrender rates, and risk-taking behavior.

Theoretically, increased stakeholder ability to monitor and discipline financial firms through public risk disclosure should motivate firms to adopt less risky management practices to avoid adverse behavioral reactions (see Crockett, 2002; Eling, 2012; Flannery & Bliss, 2019). Model-based studies suggest that insurers adjust their risk-taking behavior (e.g., capital buffers, asset allocation, reinsurance) when insurance demand is negatively related to the insurer's default risk (e.g., Blackburn et al., 2017; Eckert & Gatzert, 2018; Gründl et al., 2006; Nirmalendran et al., 2013; Rees et al., 1999; Yow & Sherris, 2008; Zanjani, 2002; Zimmer et al., 2018). However, these models often rely on theoretical assumptions or experimental findings, where default risk is made fully transparent (e.g., Wakker et al., 1997; Zimmer et al., 2009, 2018). Furthermore, they do not consider annual disclosure, as mandated by Solvency II, nor the dynamic nature of policyholders' purchase and surrender behavior over time.

Empirical research using real-market data to evaluate the impact of public risk disclosure on financial firms' risk-taking remains scarce and inconclusive (see Eling, 2012; Flannery & Bliss, 2019). One explanation for this is that asymmetric information, monitoring costs, conflicting stakeholder interests, and guarantee funds reduce the effectiveness of market discipline (see Bliss & Flannery, 2002; Deng et al., 2024; Eling, 2012). Therefore, the costs of public disclosure may outweigh the benefits of increased transparency (see Eling, 2012), leading to calls for systematic cost-benefit analyses (see Acharya & Ryan, 2016; Eling, 2021).

This paper extends previous research in several ways. We use static and dynamic panel regressions to provide the first empirical evidence of customer-driven market discipline under the Solvency II reporting regime. Focusing on Germany, the EU's largest economy, we analyze data from 58 life insurers from 2016 to 2023. We then model a life insurer's decision-making process using shareholder value maximization. While previous research has relied on run-off scenarios, theoretical assumptions, or experimental observations, our model is calibrated to align with the Solvency II framework and the empirical observations from the German market. Furthermore, we employ a multi-period asset–liability model that incorporates annual reporting and policyholders' dynamic behavior. We use a simplified Solvency II standard formula (see Boonen, 2017) to calculate the life insurer's annual solvency ratio. Based on this ratio, premiums for new policies and surrender probabilities for existing contracts are dynamically adjusted.

Our regression analyses indicate that policyholders alter their purchase and surrender behavior in response to changes in publicly reported solvency ratios. These effects are more pronounced for life insurers with lower solvency ratios and align with prior research on customer reactions to insurer rating changes (e.g., Eling & Schmit, 2012; Epermanis & Harrington, 2006). Moreover, we observe a significant increase in solvency ratios among insurers that experienced sharper declines in their ratios in the previous year, suggesting that insurers take risk-reducing actions to mitigate adverse reactions. Consistent with this, our shareholder value maximization model shows that insurers hold higher reserves when solvency ratios are publicly disclosed and policyholders respond accordingly. We observe a substantial reduction of 57.1% in the insurer's default probability. Additionally, more balanced and less risky product portfolio compositions are chosen.

These findings are helpful for insurers and regulators. They suggest that life insurers should consider insolvency-averse policyholders in their decision-making to enhance shareholder value. The results also support the case for public disclosure requirements, which may reduce insurers' risk-taking and complement regulatory oversight—provided the disclosures are accessible and understandable to customers. However, they also highlight potential limitations. Stronger policyholder reactions (e.g., given lower search costs from more risk disclosure) yield higher reserves in our model, but the reduction in default probability becomes progressively smaller and more costly. In highly competitive markets with low premium loadings, stronger policyholder reactions may even increase the insurer's default probability. Therefore, finding the right level and design of public risk disclosure seems crucial to avoid undue costs (see Eling, 2021) or unintended consequences. Finally, regulators must ensure that disclosed solvency ratios accurately reflect risk and cannot be manipulated (see Grochola & Schlütter, 2025).

The article is organized as follows: Section 2 reviews the reporting regime of Solvency II (also in comparison to other frameworks) and provides empirical evidence on the existence of customer-driven market discipline. The shareholder value maximization model is described in Section 3. Numerical results are presented in Section 4, and Section 5 concludes.

2 | PUBLIC RISK DISCLOSURE IN INSURANCE

Effective market discipline requires stakeholders to have sufficient information to monitor and discipline companies (see Crockett, 2002). Public risk disclosure can play a crucial role in this process. Section 2.1 reviews the European regulatory reporting regime under Solvency II, Section 2.2 presents empirical evidence of market discipline in the German life insurance market under Solvency II, and Section 2.3 discusses the relevance of these findings for other countries.

2.1 | European case of Solvency II

Solvency II consists of three pillars (see Gatzert & Heidinger, 2020): Pillar I defines quantitative capital requirements, including solvency capital requirements (SCRs). Pillar II addresses qualitative requirements for governance, risk management, and own risk and solvency assessments. Pillar III establishes mandatory reporting obligations to regulators and the public to enhance market discipline. These reporting obligations include quantitative key figures derived from Pillar I's capital requirements.

Under Pillar I, insurers must maintain eligible basic own funds (i.e., an excess of assets over liabilities) to cover unexpected losses from all quantifiable risks over a 1-year time period at a confidence level of 99.5% (see Directive 2009/138/EC, Article 101 (3)). Therefore, SCRs can be formalized as the value at risk of the 1-year change in basic own funds $\Delta BoF_t = BoF_{t+1} - BoF_t$ at a confidence level of 99.5%, that is,

$$P(\Delta BoF_t + SCR_t \geq 0) = 99.5\%,$$

where SCR_t denotes the SCRs at year t.

While SCR_t can be calculated using full or partial internal models, a majority (89%) of European life insurers report their SCR_t under the standard formula provided by the authorities (see Milliman, 2023). This formula divides the calculation of SCR_t into various risk (sub-)modules (see Figure A1 in the Appendix). For each risk (sub-)module, SCRs are computed as the change in basic own funds given a specified extreme event (shock), which occurs only once every 200 years (see Boonen, 2017). These individual SCRs are then aggregated under specific correlation assumptions.

The most important risk modules for life insurers are "market risk" and "life underwriting risk," which together account for approximately 84% of their SCRs (see Milliman, 2023). Consequently, we simplify the following descriptions and the model framework used in our simulation analysis in Section 3 to focus on these two modules, as in Boonen (2017). Furthermore, we consider only the "interest" and "equity" ("mortality" and "longevity") sub-modules, together accounting for approximately 70% (54%) of the module "market risk" ("life underwriting risk") (see European Insurance and Occupational Pensions Authority EIOPA, 2011). Under these simplifications, the standard formula becomes

$$SCR_t = \sqrt{SCR^2_{\text{market}} + SCR^2_{\text{life}} + 0.5 \cdot SCR_{\text{market}} \cdot SCR_{\text{life}}}, \tag{1}$$

where SCR_{market} and SCR_{life} denote the SCRs for the market and life underwriting risk modules (see Boonen, 2017).[1] The value of 0.5 represents the correlation between the two risk modules as specified in the standard formula.

To calculate SCR_{market} and SCR_{life}, separate SCRs are computed for each risk sub-module as the negative change in basic own funds given a specific shock a, that is,

$$SCR_a = \max\{-\Delta BoF \mid \text{shock } a; 0\} \; : \; a \in \{mort; long; eq; int\}. \tag{2}$$

Similar to Equation (1), SCRs of the two sub-modules are then aggregated by

$$SCR_{\text{life}} = \sqrt{SCR^2_{\text{mort}} + SCR^2_{\text{long}} + 2 \cdot Corr(mort, long) \cdot SCR_{\text{mort}} \cdot SCR_{\text{long}}} \tag{3}$$

and

$$SCR_{\text{market}} = \sqrt{SCR^2_{\text{eq}} + SCR^2_{\text{int}} + 2 \cdot Corr(eq, int) \cdot SCR_{\text{eq}} \cdot SCR_{\text{int}}}, \tag{4}$$

where $Corr(mort, long)$ and $Corr(eq, int)$ denote specific correlation parameters.

The shocks and correlation parameters are specified in the Commission Delegated Regulation (EU) 2015/35. For the mortality (longevity) risk sub-module, a 15% (20%) increase (decrease) in mortality rates is assumed, with a negative correlation parameter $Corr(mort, long) = -0.25$ between mortality and longevity risk (see Equation (3)). The equity risk sub-module assumes a 39% drop in equity prices.[2] The interest risk sub-module is defined by an instantaneous upward or downward shift in risk-free interest rates, with the worst outcome applied. The shifts in risk-free interest rates differ by maturity, with an increase of at least one percentage point.[3] The correlation parameter $Corr(eq, int)$ between equity and interest risk in Equation (4) is 0.5 for an upward shift and zero otherwise.

Under Pillar III of Solvency II, insurers must publish an annual SFCR on their website (see Gatzert & Heidinger, 2020). This report includes information on the insurer's solvency situation and follows a standardized structure with a summary and five chapters: "Business and Performance," "System of Governance," "Risk Profile," "Valuation for Solvency Purpose," and "Capital Management" as outlined in Commission Delegated Regulation (EU) 2015/35 (see also Gatzert & Heidinger, 2020). The final chapter, "Capital Management," provides details on the insurer's basic own funds BoF_t, SCRs SCR_t, and solvency ratio

$$SR_t = \frac{BoF_t}{SCR_t}, \tag{5}$$

[1]To simplify the notation, we omit the year t as an additional indicator for the SCRs of the risk (sub-)modules.

[2]The Commission Delegated Regulation (EU) 2015/35 differentiates between Type 1 equities, which are listed in the EEA or OECD, and Type 2 equities, which are not. The latter requires a higher shock of 49% (see also Boonen, 2017). An additional symmetric adjustment, calibrated on an equity index, between −10 and 10 percentage points is applied to account for pro-cyclical effects, as outlined in Article 106 of Directive 2009/138/EC. The symmetric adjustment value is published monthly by EIOPA; as of September 2023, it stands at −1.79% (see European Insurance and Occupational Pensions Authority EIOPA, 2023a).

[3]Table A1 in the Appendix shows the specified in- and decreases in risk-free interest rates across all maturities.

which must be at least 100%, as stipulated under Pillar I of Solvency II (see Gatzert & Heidinger, 2020).

This solvency ratio SR_t aims to make it relatively easy—as a single key figure—to assess and compare insurers' risk levels, which is also supported by Gatzert and Heidinger (2020). Their study showed that key figures are more influential than textual elements in assessing SFCRs. They considered different key figures in their study, but solvency ratios had the greatest impact on market reactions. Mukhtarov et al. (2022) observed that investors value the risk-based solvency ratios under Solvency II more than the volume-based ratios under Solvency I. Additionally, financial intermediaries (e.g., advisors or aggregators) pass on disclosed solvency ratios to customers. For instance, Germany's largest aggregator, Check24, displays annuity offers alongside life insurers' financial strength ratings, which are based on the disclosed solvency ratios (see Hanika & Gatzert, 2024).

2.2 | Empirical evidence on market discipline in Germany

Building on the reporting regime outlined in Section 2.1, we use publicly available data from German life insurers for the period 2016-2023 to provide empirical evidence on customer-driven market discipline under Solvency II. Solvency ratios[4] are extracted from SFCRs and supplemented with firm-level data on written premiums, costs, and surrender rates provided by the German Federal Financial Supervisory Authority (see www.bafin.de). We include all German life insurers but exclude companies with missing data, run-off companies, and small insurers with annual written premiums below 50 million Euros.[5] The final sample consists of 58 life insurers (i.e., 464 data points), comprising 42 stock companies and 16 mutual insurers.[6] In 2023, 84 life insurers operated in Germany. Our sample represents 85.12% (74.70 billion Euros) of written premiums, 82.57% (999.77 billion Euros) of assets under management, and 86.04% (3.12 trillion Euro) of the total sum insured. Table A2 in the Appendix provides summary statistics for the regression sample from 2016 to 2023, compared to the entire German life insurance market.

Figure 1 illustrates the evolution of solvency ratios for the sample of 58 life insurers. These ratios vary considerably between companies, as indicated by the interquartile range, and also fluctuate over time. Since the publication of the first SFCRs for the 2016 fiscal year, solvency ratios have increased, with a temporary decline from 2018 to 2020. The largest decrease is between 2019 and the onset of the COVID-19 pandemic in 2020. The lower median solvency ratio compared to the mean solvency ratio results primarily from three life insurers with exceptionally high average solvency ratios of 582%, 661%, and 870% over the 8-year period.

The high solvency ratios—especially in comparison to European peers (see Milliman, 2023)—suggest that German life insurers are well-capitalized. However, the sample also includes two life insurers with mean solvency ratios of 32% and 47% over the 8-year period,

[4]We analyze solvency ratios without transitional or adjustment measures, as they provide a more accurate assessment of life insurers' risk levels. For a detailed discussion, see Gatzert and Heidinger (2020).

[5]One additional life insurer, HanseMerkur Lebensversicherung AG, was excluded due to an abnormal group-level management decision to reduce single premium business, which led to an approximately 71% decrease in the insurer's written premiums between 2021 and 2022.

[6]The group of mutual insurers includes four public-law insurers, mandated by state authorities to serve public interests and focus on community service rather than profit generation.

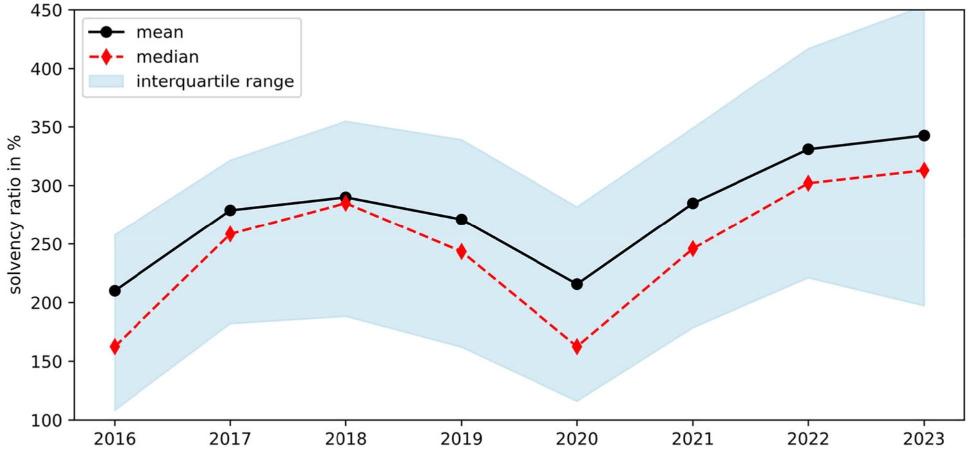

FIGURE 1 Solvency ratios for the sample of 58 German life insurers from 2016 to 2023.

which only met the regulatory minimum solvency requirement of 100% by utilizing transitional measures (see Grochola & Schlütter, 2025). Furthermore, the insolvency of the German holding company FWU in 2024 and the subsequent liquidation of its Luxembourgish subsidiary, FWU Life Insurance, impacted numerous policyholders across Europe, generating uncertainty regarding the status of their investments and insurance policies (see European Insurance and Occupational Pensions Authority EIOPA, 2024).

To study the impact of changes in insurers' reported risk levels on policyholders' dynamic purchase and surrender behavior (i.e., the monitoring dimension of market discipline), we follow previous research and conduct regression analyses (see Eling & Schmit, 2012; Epermanis & Harrington, 2006). Our dependent variables are the log premium growth $\Delta P_{i,t} = \ln(P_{i,t}/P_{i,t-1})$ and the log change in surrender rates $\Delta\Pi_{i,t} = \ln(\Pi_{i,t}/\Pi_{i,t-1})$. The variable $P_{i,t}$ represents gross written premiums, and $\Pi_{i,t}$ the surrender rate of firm i in year t.[7] To align our analysis with Solvency II, we consider the log change in reported solvency ratios $\Delta SR_{i,t-1} = \ln(SR_{i,t-1}/SR_{i,t-2})$ from the previous year as the independent variable of interest. The log premiums $P^*_{i,t} = \ln(P_{i,t})$ and the log change in costs $\Delta Costs_{i,t} = \ln(Costs_{i,t}/Costs_{i,t\text{-}1})$ serve as control variables, where $Costs_{i,t}$ account for acquisition and running costs in year t, measured as a percentage of gross written premiums.

We run linear fixed effects regression models with firm fixed effects, calculate robust standard errors (clustered at the firm level) to avoid distorted significance levels, and include dummy variables for year effects (see, e.g., Epermanis & Harrington, 2006). This results in the following two regression models:

$$\Delta P_{i,t} = \beta_0 + \beta_1 \cdot P^*_{i,t} + \beta_2 \cdot \Delta \mathrm{Costs}_{i,t} + \beta_3 \cdot \Delta SR_{i,t-1} + \nu^T \Theta + \zeta_i + \varepsilon_{i,t}, \tag{R1}$$

$$\Delta \Pi_{i,t} = \beta_0 + \beta_1 \cdot P^*_{i,t} + \beta_2 \cdot \Delta \mathrm{Costs}_{i,t} + \beta_3 \cdot \Delta SR_{i,t-1} + \nu^T \Theta + \zeta_i + \varepsilon_{i,t}, \tag{R2}$$

[7]The surrender rate measures early terminations, surrenders, and conversions to paid-up policies, expressed as a percentage of the sum insured within the insurer's portfolio.

where Θ denotes a vector of year dummies with parameter vector ν, ζ_i represents firm fixed effects, and $\varepsilon_{i,t}$ is a mean-zero disturbance.

To analyze the influencing dimension of market discipline, we examine whether life insurers with greater declines in solvency ratios demonstrate stronger increases in solvency ratios the following year. This could suggest that life insurers take reactive management actions to prevent negative behavioral reactions from policyholders.[8] We use the log change in solvency ratios $\Delta SR_{i,t}$ in year t as the dependent variable and replace the independent variable $\Delta SR_{i,t-1}$ by $\Delta SR_{i,t-1}^{\text{down}} = -\min\{\Delta SR_{i,t-1}; 0\}$, i.e.,

$$\Delta SR_{i,t} = \beta_0 + \beta_1 \cdot P_{i,t}^{*} + \beta_2 \cdot \Delta \text{Costs}_{i,t} + \beta_3 \cdot \Delta SR_{i,t-1}^{\text{down}} + \nu^T \Theta + \zeta_i + \varepsilon_{i,t}. \tag{R3}$$

The correlation matrix and variance inflation factors, along with descriptive statistics for the variables in regression models (R1,R2,R3), are presented in Tables A3–A5 in the Appendix.

To account for possible differences in policyholder reactions between life insurers with lower and higher solvency ratios (see Epermanis & Harrington, 2006), we consider a variant for all three regression models (R1,R2,R3). Specifically, we multiply $\Delta SR_{i,t-1}$ in models (R1,R2) and $\Delta SR_{i,t-1}^{\text{down}}$ in model (R3) by the dummy variables $Upper_{i,t-1}^{50\%}$ and $Lower_{i,t-1}^{50\%}$, which take one if the solvency ratio of life insurer i was among the highest (lowest) 50% of all solvency ratios in year $t-1$. To address potential endogeneity issues in the fixed effects models (R1,R2,R3), such as those caused by the use of lagged variables,[9] we run dynamic panel regressions as a robustness check. Specifically, we included the lagged premium growth $\Delta P_{i,t-1}$ in models (R1,R2,R3) and the lagged change in surrender rate $\Delta \Pi_{i,t-1}$ in model (R2) as independent variables, employing the two-step system GMM estimation process (see Blundell & Bond, 1998). As before, we include-year dummies for year effects and calculate robust standard errors clustered at the firm level. The instrumental variables in models (R1,R2) are constructed using the log change in costs lagged by one or more years, as well as the respective dependent variable, and the log change in solvency ratio lagged by two or more years. In model (R1), we also add the log premiums lagged by two or more years as instruments. In model (R3), the instrumental variables include the log change in costs lagged by one or more years, as well as the log premium growth, the log decrease in solvency ratio, and the log change in surrender rate lagged by two or more years.

While the two-step system GMM estimation process is designed to mitigate weak instruments by using a system of two equations with lagged variables and lagged differences as instruments (see Blundell & Bond, 1998), the use of too many instruments can bias results and affect diagnostic tests (see Bazzi & Clemens, 2013; Roodman, 2009). Therefore, we follow best practices by collapsing instruments to reduce their number. To identify potentially weak instruments, we assess first-stage F-statistics for all independent variables by extracting the internally created variable and instrument matrices of the system GMM estimator to run a two-stage least squares regression (see Bazzi and Clemens (2013) for a similar approach). While the first-stage F-statistics for all independent variables exceed 10, we acknowledge that the risk of weak instruments cannot be completely ruled out. Therefore, the results should be interpreted with caution.

[8]According to Equation (5), higher solvency ratios can be achieved either by increasing basic own funds or by decreasing the SCRs.

[9]A commonly discussed issue with fixed effects models is the use of a lagged dependent variable, which can lead to Nickell bias (see Nickell, 1981). This is especially problematic for our analysis due to the relatively short time horizon of $T = 8$.

The results for the fixed effects model (R1) and the respective system GMM are shown in Table 1. The estimated coefficients indicate a positive impact of the log change in solvency ratio $\Delta SR_{i,t-1}$ on the log premium growth $\Delta P_{i,t}$. However, the estimated coefficients are only (weakly) statistically significant (p-values of 0.032 and 0.0740) for life insurers with the lowest 50% solvency ratios (as indicated by the dummy variable $Lower^{50\%}_{i,t-1}$). For life insurers with the highest 50% solvency ratios, the estimated coefficients are negative and not statistically significant. Thus, policyholders appear to increase (decrease) their demand in response to a life insurer's increased (decreased) solvency ratio, but this effect is present only for insurers with lower solvency ratios.

Similar results are observed for model (R2) regarding the impact on the log change in surrender rate $\Pi_{i,t}$ (see Table A6 in the Appendix). For the system GMM, the estimated coefficient of $\Delta SR_{i,t-1}$ is negative (p-value of 0.0321), indicating that a decrease (increase) in a life insurer's solvency ratio is associated with higher (lower) surrender motivation from policyholders. This effect is more pronounced (p-value of 0.0031) for life insurers with lowest 50% solvency ratios (as indicated by the dummy variable $Lower^{50\%}_{i,t-1}$) and not present for life insures with 50% highest solvency ratios. The results of the fixed effects model are not statistically significant.

Our findings align with previous research on policyholder reactions to rating changes of life insurers (e.g., Eling & Schmit, 2012). They suggest that policyholders adjust their purchase and

TABLE 1 Results of model (R1) with log premium growth as the dependent variable.

	Fixed effects		System GMM	
Variables	**Variant 1**	**Variant 2**	**Variant 1**	**Variant 2**
$P^*_{i,t}$	0.1385 (0.1046)	0.1347 (0.1051)	0.0304 (0.0585)	−0.0302 (0.0211)
$\Delta Costs_{i,t}$	−0.3597*** (0.0814)	−0.3596*** (0.0791)	−0.4080*** (0.0841)	−0.3969*** (0.0833)
$\Delta SR_{i,t-1}$	0.0106 (0.0151)		0.0028 (0.0140)	
$\Delta SR_{i,t-1} \times Lower^{50\%}_{i,t-1}$		0.0237** (0.0110)		0.0213* (0.0119)
$\Delta SR_{i,t-1} \times Upper^{50\%}_{i,t-1}$		−0.0350 (0.0327)		−0.0015 (0.0245)
$\Delta P_{i,t-1}$			0.2273*** (0.0736)	0.2612*** (0.0701)
R^2 (within)	0.4277	0.4386		
Sargan-Hansen test (p-value)			0.5452	0.5268
Arellano-Bond test AR(1) (p-value)			0.0013	0.0008
Arellano-Bond test AR(2) (p-value)			0.4471	0.4256
Num firms			58	
Num observations			348	

Note: The table shows estimated coefficients and robust standard errors (clustered at the firm level) in brackets. Year dummies are included, but not reported. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The variable $\Delta Costs_{i,t}$ defines the log change in costs, $\Delta SR_{i,t-1}$ is the log change in solvency ratio, and $P^*_{i,t}$ is the log premiums. The dummy variables $Upper^{50\%}_{i,t-1}$ and $Lower^{50\%}_{i,t-1}$ take one if the solvency ratio is among the 50% highest or lowest of all solvency ratios, respectively.

surrender behavior in response to positive (negative) changes in a life insurer's risk level. These reactions appear only to be limited to life insurers with lower solvency ratios, where policyholders may be more concerned about the financial stability of the insurer. This is also supported by the experimental findings of Hanika and Gatzert (2024), who found that customers react more strongly to changes in financial strength ratings when ratings are lower. Similarly, Epermanis and Harrington (2006) observed larger premium declines following credit rating downgrades for insurers with lower ratings before the downgrade.

Regarding the influencing dimension of market discipline, we find evidence that life insurers respond to a decline in their solvency ratio by improving it in the subsequent year, likely through reactive management actions (see Table 2). For both the fixed effects and system GMM models, the estimated coefficients of $\Delta SR_{i,t-1}^{\text{down}}$ in model (R3) are positive and statistically significant (p-values of < 0.001 and 0.033). As before, this effect is more pronounced for life insurers with lower solvency ratios and is absent for life insurers with higher solvency ratios, where the estimated coefficients of $\Delta SR_{i,t-1}^{\text{down}} \times Upper_{i,t-1}^{50\%}$ are negative and not statistically significant. One explanation could be the expectedly more pronounced behavioral reactions of customers when life insurers have lower solvency ratios (i.e., customer-driven market discipline). A robustness test, where we replaced $\Delta SR_{i,t-1}^{\text{down}}$ by the log change in solvency ratio $\Delta SR_{i,t-1}$ and by the log increase in solvency ratio $\Delta SR_{i,t-1}^{\text{up}} = \max\{\Delta SR_{i,t}; 0\}$ as independent

TABLE 2 Results of model (R3) with the log change in solvency rate as the dependent variable.

	Fixed effects		System GMM	
Variables	**Variant 1**	**Variant 2**	**Variant 1**	**Variant 2**
$P_{i,t}^{*}$	−0.3144*** (0.1103)	−0.2697** (0.1052)	−0.0099 (0.0097)	−0.0092 (0.0090)
$\Delta Costs_{i,t}$	−0.2035 (0.2134)	−0.2241 (0.2090)	−0.1150 (0.2059)	−0.1736 (0.2076)
$\Delta SR_{i,t-1}^{\text{down}}$	0.5363*** (0.0776)		0.1754** (0.0821)	
$\Delta SR_{i,\,t\text{-}1}^{down} \times Lower_{i,t\text{-}1}^{50\%}$		0.5654*** (0.0729)		0.2239*** (0.0835)
$\Delta SR_{i,\,t\text{-}1}^{down} \times Upper_{i,t\text{-}1}^{50\%}$		−0.0205 (0.1401)		−0.2820 (0.2043)
$\Delta P_{i,t-1}$			0.0313 (0.3136)	0.1201 (0.3805)
R^2 (within)	0.3970	0.4074		
Sargan–Hansen test (p-value)			0.5505	0.4739
Arellano–Bond test AR(1) (p-value)			<0.0001	<0.0001
Arellano–Bond test AR(2) (p-value)			0.0917	0.0817
Num firms	58			
Num observations	348			

Note: The table shows estimated coefficients and robust standard errors (clustered at the firm level) in brackets. Year dummies are included, but not reported. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The variable $\Delta Costs_{i,t}$ defines the log change in costs, $\Delta P_{i,t-1}$ is the log premium growth, $SR_{i,t-1}^{\text{down}}$ is the log decrease in solvency ratio, and $P_{i,t}^{*}$ represents the log premiums. The dummy variables $Upper_{i,t-1}^{50\%}$ and $Lower_{i,t-1}^{50\%}$ take one if the solvency ratio is among the 50% highest or lowest of all solvency ratios, respectively.

variable in model (R3) and observed only weak[10] and no statistically significant results (see Table A7 in the Appendix), supports this conclusion.

Other explanations for life insurers increasing their solvency ratios after a decline could include fear of behavioral reactions from investors (i.e., investor-driven market discipline) or regulatory interventions, especially when approaching the regulatory solvency threshold of 100%. To explore these possibilities, we conduct two additional regression analyses (see Table A8 in the Appendix). In Variant 1, we multiply the log decrease in solvency ratio $\Delta SR_{i,t-1}^{\text{down}}$ in model (R3) by the dummy variables $Stock_i$ and $Mutual_i$ to separately investigate the impact for stock and mutual companies. In Variant 2, we add a dummy variable $Critical_{i,t-1}$ to control for life insurers with solvency ratios of below 110% (i.e., slightly above or below the regulatory threshold of 100%). In both variants, the results from Table 2 remain valid. The estimated coefficients for $\Delta SR_{i,t-1}^{\text{down}} \times Stock_i$ and $\Delta SR_{i,t-1}^{\text{down}} \times Mutual_i$ are all positive and statistically significant (p-values of < 0.001) in the fixed effects models, with the impact higher for mutual companies. For the system GMM models, the estimated coefficients are slightly higher for the stock companies, but only the coefficients for the mutual companies are statistically significant (p-values of 0.005 and 0.040). Moreover, the impact diminishes only slightly when controlling for life insurers with solvency ratios below 110%. Therefore, our observations suggest that the increased solvency ratios are not primarily driven by investors or regulators. They even suggest that conflict of interests between customers and investors, where the latter may focus more on profit generation than increasing solvency ratios, might reduce the effectiveness of market discipline in the German life insurance market. This seems plausible given the higher solvency ratios in Germany compared to other countries (see Milliman, 2023). Bliss and Flannery (2002) argue similarly about the conflicting interests between stock- and bondholders, which reduce market discipline in the banking sector.

2.3 | Relevance for other insurance markets

The results from Section 2.2 indicate the existence of customer-driven market discipline in the German life insurance market under Solvency II's public reporting regime. This finding is relevant for many other countries, as Solvency II applies across all 27 EU member states, as well as Iceland, Liechtenstein, and Norway. Including the UK,[11] these countries represent approximately 30% of the global life insurance premium volume (see Swiss Re, 2024).

Although solvency ratios are calculated and publicly disclosed in a harmonized way under Solvency II, several factors may influence the effectiveness of market discipline. For instance, solvency ratios disclosed by life insurers vary greatly between countries, with Germany exhibiting the highest ratios (see Milliman, 2023). Given our finding that market reactions are limited to life insurers with lower solvency ratios (see Section 2.2), this variation may affect market discipline. Furthermore, national-level guarantee schemes could create moral hazard

[10]The only statistically significant result (p-value = 0.063) can be seen for $\Delta SR_{i,t-1}$ in the fixed effects model, which may also be influenced by Nickell bias (see Nickell, 1981).

[11]The UK left the EU in January 2020 and is currently adapting Solvency II to establish its own insurance solvency regime (see Müller & Reuse, 2023; Rae et al., 2018). Market discipline, particularly the SFCR, will remain in place, but the scope of disclosure will be reduced and more specifically tailored to policyholders.

effects and weaken market discipline (see Deng et al., 2024; Eling, 2012).[12] These schemes exist in 20 out of 31 European countries but differ greatly in scope and coverage (see European Insurance and Occupational Pensions Authority EIOPA, 2018). In Germany, for example, the guarantee fund “Protektor Lebensversicherungs-AG” safeguards policyholders if their life insurer defaults (see Bundesanstalt für Finanzdienstleistungsaufsicht BaFin, 2025). Future research should investigate how these country-specific factors influence market discipline under Solvency II.

Beyond Solvency II, several international regulatory frameworks share similarities, with Bermuda and Switzerland achieving full equivalence (see European Insurance and Occupational Pensions Authority EIOPA, 2025). In Switzerland, insurers are required to publish an annual financial condition report, structured similarly to SFCRs, which provides qualitative and quantitative information about solvency and must be written in a manner that is accessible to policyholders (see Financial Market Supervisory Authority FINMA, 2016). Other countries, such as Japan (see Deloitte, 2022; Park & Tokutsune, 2013) and China (see Fung et al., 2018), have adopted a three-pillar approach as in Solvency II, where solvency ratios are calculated under Pillar I and publicly disclosed under Pillar III. The US, the world's largest insurance market, does not follow Solvency II's three-pillar structure. US insurers are subject to risk-based capital (RBC) requirements and report their RBC ratios to state regulators (see Lindberg & Seifert, 2015). However, these ratios are often not publicly disclosed in a format accessible to policyholders, demonstrating that public solvency disclosure and market discipline play varying roles across different regulatory regimes (see Fung et al., 2018).

The question of whether more comprehensive and harmonized disclosure strengthens market discipline remains largely unexamined (see Eling, 2012). Dong (2014) provides empirical evidence suggesting that increased disclosure (measured by the number of publicly available documents) positively influences the ex-ante risk decisions of European insurers. Additionally, the findings by Park and Tokutsune (2013) suggest that our observations from the German market (see Section 2.2) may apply to other markets with similar solvency regimes. They found that changes in publicly disclosed solvency ratios of foreign life insurers in Japan influence premium growth and surrender rates. However, similar results have been observed for rating changes of insurers in the US (see Epermanis & Harrington, 2006) or Germany before the introduction of Solvency II (see Eling & Schmit, 2012). This raises the question of whether public solvency disclosure, as mandated by Solvency II, is necessary. Future research could utilize differences in regulatory frameworks to analyze their impact on market discipline.

A major limitation of financial ratings compared to mandatory solvency disclosure is that they are not available for all insurance companies, involve costs and potential conflicts of interest, and primarily cater to investors rather than policyholders. In contrast, the upcoming Solvency II review will introduce a split in the SFCR into two reports in the future (see Directive (EU) 2025/2, Article 1 (25)): a simplified version for policyholders and a more comprehensive, technical version for investors. This change could improve the information content for policyholders and further strengthen market discipline. Finally, public solvency disclosure can improve the ratings provided by agencies (see Lindberg & Seifert, 2015; Rae et al., 2018).

[12]Note that in life insurance, most research finds no or only a weak impact of guarantee funds on the effectiveness of market discipline (see Grace et al., 2019; Li et al., 2021; Searle et al., 2024).

3 | MODEL FRAMEWORK

Motivated by the empirical findings in Section 2.2, we now develop a model-based approach to investigate how policyholders' behavioral responses to reported solvency ratios influence a life insurer's risk-taking behavior. Empirically, this relationship would be difficult to analyze, as insurers' managerial decisions are shaped by many intertwined factors that would need to be carefully controlled for in real-world data. In a theoretical model, we can isolate and focus on the key mechanisms (annual solvency disclosure, dynamic purchase and surrender behavior, management options), while controlling for other aspects. However, the results will inevitably rely on some simplifications and assumptions. The model thus aims to strike an effective balance between complexity and tractability to offer meaningful and interpretable results. The following subsections first provide an overview of the model framework. Then, we describe the model on a technical level, including the asset and mortality models, the life insurer's asset–liability model, the reporting mechanism with policyholders' behavioral reactions, the risk assessment, and shareholder value maximization.

3.1 | Model framework in a nutshell

As illustrated in Figure 2, the core of our model is shareholder value maximization, built upon a life insurer's multi-period asset–liability model. The insurer annually sells term life insurance contracts and temporary annuities to policyholders. The model aligns with the risk measurement and reporting regime of Solvency II (see Section 2.1). At the end of each year, the insurer publicly reports its solvency ratio, calculated using the simplified Solvency II standard formula (see Equations (1) and (5)). Calibrated to the empirical observations from Section 2.2, policyholders adjust their purchase behavior for new business and surrender behavior for existing contracts in response to this reported solvency ratio.

To assess whether these behavioral reactions of policyholders could (partially) explain the reduction in life insurer's risk-taking, observed in Section 2.2 (i.e., their motivation to increase solvency ratios following a decline), the model incorporates several management options:

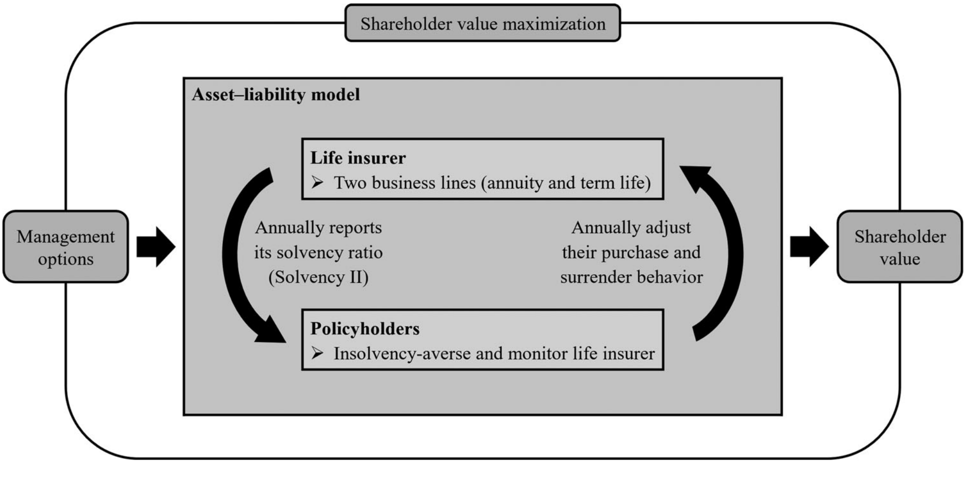

FIGURE 2 Illustration of the model framework.

Reserves, asset allocation, and product portfolio composition. These management decisions influence the reported solvency ratio and, consequently, policyholders' purchase and surrender behavior. Less risky management actions increase the life insurer's premium income, but incur costs. For instance, holding additional reserves limits dividend payments to shareholders, and less risky asset allocations reduce expected returns.[13] Consequently, shareholder value is affected in various ways. By maximizing shareholder value, we can evaluate whether the life insurer would opt for less risky behavior to mitigate negative reactions from policyholders, or whether the opportunity costs would deter such actions.

3.2 | Asset and mortality model

The asset model accounts for equity and interest rate risks, as addressed in Section 2.1. We model stock prices and short-term interest rates using stochastic dynamics (see Nirmalendran et al., 2013). The short rates represent risk-free rates in our model. Stock prices X_t evolve over time t according to a geometric Brownian motion, that is,

$$dX_t = \mu_X \cdot X_t \, dt + \sigma_X \cdot X_t \, dW_t^X \tag{6}$$

with drift μ_X, volatility σ_X, and standard Brownian motion W_t^X. The solution of the stochastic differential equation is given by

$$X_t = X_{t-1} \cdot \exp\left(\mu_X - \frac{\sigma_X^2}{2} + \sigma_X \cdot \varepsilon_t^X\right) = X_{t-1} \cdot \exp\left(r_t^X\right),$$

where ε_t^X are independent and identically distributed standard normally distributed random variables, and r_t^X denotes the continuous one-period return of a stock investment (see, e.g., Bohnert et al., 2015).

For the evolution of short rates r_t^{SR} over time t, we follow Nirmalendran et al. (2013) and employ the Vasicek model, that is,

$$dr_t^{SR} = \kappa \cdot \left(\mu_{SR} - r_t^{SR}\right) dt + \sigma_{SR} \, dW_t^{SR}, \tag{7}$$

where κ denotes the speed of adjustment to the long-term value μ_{SR}, σ_{SR} is the volatility, and W_t^{SR} is a standard Brownian motion. As Solvency II requires market-consistent valuations of insurers' liabilities (see Boonen, 2017), we use the closed-form solution of the Vasicek model for zero-coupon bond prices (see Vasicek, 1977) to derive discount factors. At time t, the discount factor $v(t, s)$ for a payment in $s > t$ (see also Nirmalendran et al., 2013) is given by

$$v(t, s) = \exp\left(-F(t, s) \cdot r_t^{SR} - G(t, s)\right), \tag{8}$$

[13]Note that cutting dividends is a strategy employed by life insurers to boost capital levels, as seen during the financial crisis (see Berry-Stölzle et al., 2014).

where

$$F(t,s) = \frac{1}{\kappa} \cdot (1 - \exp(-\kappa \cdot (s-t))) \text{ and}$$
$$G(t,s) = \left(\mu_{SR} + \frac{\lambda \cdot \sigma_{SR}}{\kappa} - \frac{\sigma_{SR}^2}{2 \cdot \kappa^2}\right) \cdot ((s-t) - F(t,s)) + \frac{\sigma_{SR}^2}{4 \cdot \kappa} \cdot F(t,s)^2$$

with λ denoting the market price of risk.

Extending Gründl et al. (2006), the insurer's return on assets r_t is modeled as a convex combination of risk-free and risky investments. We use the short rates r_t^{SR} generated by the Vasicek model for single-period returns on risk-free investments and 1-year stock returns r_t^X for the risky investment, that is,

$$r_t = \alpha \cdot r_t^{SR} + (1-\alpha) \cdot r_t^X \tag{9}$$

with α representing the proportion of assets invested at the risk-free rate. Furthermore, we assume that both investments are correlated, with $\rho = \rho\left(W_t^X, W_t^{SR}\right)$ denoting the correlation coefficient between the two standard Brownian motions in Equations (6) and (7).

The mortality model builds on Gatzert and Wesker (2012). The mortality rates of x-year-old policyholders $m(x,t)$ follow the Lee–Carter model

$$m(x,t) = \exp\left(a_x + b_x \cdot k_t + \varepsilon_{x,t}^m\right), \tag{10}$$

where a_x and b_x are age-specific constants, k_t is the time trend, and $\varepsilon_{x,t}^m$ represents homoscedastic error terms with mean zero (see Lee & Carter, 1992). The time trend k_t is modeled by a random walk with drift, $k_{t+1} = k_t + \phi + \varepsilon_t^{RW}$, where ϕ denotes the drift and ε_t^{RW} is a Gaussian white noise process with standard deviation σ_{RW} (see Gatzert & Wesker, 2012; Lee & Carter, 1992).

The mortality rates in Equation (10) are converted to 1-year survival probabilities of x-year-old individuals in year t by $p_x(t) = \exp(-m(x,t))$ (see Brouhns et al., 2002). One-year death probabilities are computed by $q_x(t) = 1 - p_x(t)$ and n-year survival probabilities by ${}_n p_x(t) = \prod_{k=0}^{n-1} p_{x+k}(t+k)$. Furthermore, we extend the Lee–Carter model, following Brouhns et al. (2002) and draw the number of deaths $D(x,t)$ of x-year-old persons in year t from the Poisson distribution

$$D(x,t) \sim Poisson(E(x,t) \cdot \hat{m}(x,t)) \text{ with } \hat{m}(x,t) = \exp(a_x + b_x \cdot k_t). \tag{11}$$

The variable $E(x,t)$ denotes the exposure-to-risk, i.e., the number of individuals at risk of dying at age x during year t.

3.3 | Life insurer model

The life insurer's asset–liability model follows the setting in Gatzert and Wesker (2012), extended to include annual new business, additional premium loadings, and contract surrenders. The model covers two business lines: annuities and term life insurance with a time horizon of T years.

Premiums are paid at the beginning and payments to policyholders at the end of each year t, where t^+ represents the beginning, and t^- the end. At the start of each year, n contracts are sold, divided into $n_R = \lceil n \cdot \theta \rceil$ temporary annuities and $n_S = \lfloor n \cdot (1-\theta) \rfloor$ term life insurance policies, with θ denoting the fraction of annuities. Annuities and term life insurance policies are sold to policyholders with age x_R and x_S, respectively. All contracts are fairly priced with an additional loading ω, have a contract term of T years, and have the same actuarial present value M.

Temporary annuities are sold against single premiums SP_R, and term life insurance policies against annual premiums P_S. The former provides an annuity R until the policyholder's death or maturity, and the latter provides a death benefit S in the event of the policyholder's death. As the actuarial present values are equal to M for all contracts, but mortality and interest rates vary over time (see Section 3.2), R and S depend on the year of purchase. Furthermore, as policyholders' willingness to pay is affected by the insurer's annually disclosed solvency ratio, explained in Section 3.4, the premiums SP_R and P_S also depend on the year of purchase. Therefore, the pricing formulas for products sold at t^+ are given by

$$SP_R(t) = (1+\omega) \cdot R(t) \cdot \sum_{k=1}^{T} {}_k p_x(t) \cdot v(t, t+k) = M \tag{12}$$

and

$$\begin{aligned} P_S(t) \cdot \sum_{k=0}^{T-1} {}_k p_x(t) \cdot v(t, t+k) \\ = (1+\omega) \cdot S(t) \cdot \sum_{k=0}^{T-1} {}_k p_x(t) \cdot q_{x+k}(t+k) \cdot v(t, t+k+1) = M. \end{aligned} \tag{13}$$

To calculate a contract's value at the end of a year (i.e., at t^-), we introduce a second time index $\tau \leq t$. For a specific contract, it describes the year in the past, when the contract was bought by a policyholder at age x.[14] At t^-, this policyholder is then $x+t-\tau+1$ years old with the contracts' maturity in $T-t+\tau-1$ years. As a result, the value at t^- of a single annuity bought in year $\tau \leq t$ is

$$V_R^-(t,\tau) = R(\tau) \cdot \sum_{k=1}^{T-t+\tau-1} {}_k p_{x+t-\tau+1}(t+1) \cdot v(t+1, t+k+1). \tag{14}$$

Analogously, and accounting for the annual premiums of term life insurance, the value at t^- of a single term life insurance policy bought in year $\tau \leq t$ is

$$\begin{aligned} V_S^-(t,\tau) = S(\tau) \cdot \sum_{k=0}^{T-t+\tau-2} {}_k p_{x+t-\tau+1}(t+1) \cdot q_{x+t-\tau+1+k}(t+k+1) \cdot v(t+1, t+k+2) \\ - P_S(\tau) \cdot \sum_{k=0}^{T-t+\tau-2} {}_k p_{x+t-\tau+1}(t+1) \cdot v(t+1, t+k+1). \end{aligned} \tag{15}$$

[14]Note that contracts are bought at the beginning of a year, but valued at the end of a year.

Finally, the surrender value at t^- of a contract $i \in \{R, S\}$ (bought in year τ) is the contract's current value reduced by a surrender fee c, that is,

$$SV_i^-(t,\tau) = (1-c)\cdot V_i^-(t,\tau).$$

At time $t = 1^+$, the life insurer is founded, shareholders make some initial contribution E_0, and the first n_R annuities and n_S term life insurance policies are sold. Therefore, the life insurer's initial assets are given by

$$A_{1^+} = E_0 + n_R \cdot SP_R(1) + n_S \cdot P_S(1).$$

To describe the life insurer's payment obligations, let $d_R(t,\tau)$ or $d_S(t,\tau)$ denote the number of policyholders who bought an annuity or term life insurance contract at the beginning of year τ and died during year t. Analogously, let $c_R(t,\tau)$ or $c_S(t,\tau)$ denote the number of canceled annuities or term life insurance policies during year t, bought at the start of year τ. Then,

$$n_i^-(t,\tau) = \begin{cases} n_i - \ d_i(t,\tau) - c_i(t,\tau) & \text{if } t = \tau \\ n_i - \sum_{k=\tau}^{t} (d_i(k,\tau) + c_i(k,\tau)) & \text{else} \end{cases}$$

defines the number of active contracts at t^- with $i \in \{R, S\}$, and τ is the year of purchase.

Accounting for the return on assets r_t in Equation (9) and payment obligations toward policyholders, the life insurer's adjusted assets at t^- are

$$\begin{aligned} A_{t^-}^{\text{adj}} = A_{t^+} \cdot \exp(r_t) - \sum_{\tau \le t} S(\tau)\cdot d_S(t,\tau) - \sum_{\tau \le t} SV_S^-(t,\tau)\cdot c_S(t,\tau) \\ - \sum_{\tau \le t} R(\tau)\cdot n_R^-(t,\tau) - \sum_{\tau \le t} SV_R^-(t,\tau)\cdot c_R(t,\tau). \end{aligned}$$

The required policy reserves at t^- derive from the accumulated cash values of all active contracts, as expressed in Equations (14) and (15), that is,

$$PR_{t^-} = \sum_{\tau \le t} \Big(n_S^-(t,\tau)\cdot V_S^-(t,\tau) + n_R^-(t,\tau)\cdot V_R^-(t,\tau) \Big).$$

Therefore, $B_{t^-} = A_{t^-}^{\text{adj}} - PR_{t^-}$ defines the life insurer's generated surplus.

If B_{t^-} is negative, the insurer defaults, available assets are distributed to policyholders, and all contracts end prematurely. If the surplus is positive, the portion β (the buffer ratio) is retained as additional capital reserves beyond the policy reserves. The remaining fraction $(1-\beta)$ is distributed to shareholders as an annual dividend $div(t) = (1-\beta)\cdot B_{t^-}$, which means that the life insurer's final assets are $A_{t^-} = A_{t^-}^{\text{adj}} - (1-\beta)\cdot B_{t^-}$ and basic own funds are $BoF_{t^-} = A_{t^-} - PR_{t^-}$ at the end of year t. Furthermore, let SCR_{t^-} denotes the life insurer's SCRs calculated according to the simplified Solvency II standard formula in

Equations (1)–(4).[15] Thus, $SR_{t^-} = BoF_{t^-} \,/\, SCR_{t^-}$ (see Equation (5)) defines the life insurer's solvency ratio at the year-end. With premium income from new business and active term life insurance policies, the insurer's assets at the beginning of the following year $t + 1$ are given by

$$A_{(t+1)^+} = A_{t^-} + n_R \cdot SP_R(t+1) + n_S \cdot P_S(t+1) + \sum_{\tau \le t} n_S^-(t,\tau) \cdot P_S(\tau).$$

3.4 | Policyholders' behavioral reactions

In line with Solvency II, the life insurer annually discloses its solvency ratio SR_{t^-} for the year-end t^-, with an initially expected solvency ratio of $SR_{0^-} = 225\%$. This value corresponds to the median solvency ratio in the EU (see European Insurance and Occupational Pensions Authority EIOPA, 2023b). As policyholders are insolvency-averse, the reported solvency ratio influences their purchase and surrender behavior in the following year $t + 1$. We assume that these behavioral responses influence the level of premiums of new business and the surrender probability of existing contracts. The annual adjustments to the premium levels and surrender probabilities are calibrated on the regression results presented in Section 2.2 and modeled as follows.

To model the policyholders' adjusted willingness to pay in year t, we multiply the single premiums $SP_R(t)$ for annuities (see Equation (12)) and the annual premiums $P_S(t)$ for term life insurance policies (see Equation (13)) by an additional premium factor $L_t^p(\xi)$. This factor depends on the solvency ratio of the year-end of the previous year $SR_{(t-1)^-}$ and a policyholder reaction parameter ξ.[16] To represent $L_t^p(\xi)$, we build on the regression results from Section 2.2, that is, the estimated impact of the log change in the solvency ratio on the log change in premiums (see Table 1). As no statistically significant impact was observed for life insurers with the 50% highest solvency ratios, we set $L_t^p(\xi) = 1$ if the solvency ratio $SR_{(t-1)^-}$ lies above the market's median and initially expected value of 225%. In the other case, we exponentially (i.e., linear in log rate) decrease the premiums depending on the log change in solvency ratio compared with the reference value of 225%, weighted by the estimated coefficient of 0.0213 from Table 1 and policyholders' risk sensitivity ξ.[17] As a result, for all years $t \geq 1$ the premium factors are

$$L_t^p(\xi) = \begin{cases} \exp\left(0.0213 \cdot \xi \cdot \ln\left(\frac{S_{t-1}}{225\,\%}\right)\right) & \text{if} \quad S_{t-1} < 225\% \\ 1 & \text{else.} \end{cases} \tag{16}$$

[15]To obtain the changes in basic own funds ΔBoF in Equation (2), we apply the shocks outlined in Section 2.1: For the mortality and longevity shock, we compute the change in policy reserves PR_{t^-} when mortality rates are increased or decreased by 15% or 20%, respectively. For the equity shock, we reduce the assets invested in stocks $(1-\alpha) \cdot A_{t^-}$ by $39\% - 1.79\% = 37.21\%$ accounting for the symmetric adjustment. For the interest rate shock, we calculate how the policy reserves PR_{t^-} and the assets invested risk-free $\alpha \cdot A_{t^-}$ change when risk-free interest rates are adjusted according to Table A1 in the Appendix. Finally, we reduce SCR_t by 40% to reflect the loss-absorbing capacity of technical provisions and deferred taxes, approximating the observed value in practice (see Milliman, 2023).

[16]The policyholder reaction parameter ξ can be interpreted as risk sensitivity, inverse search costs, or the salience of the life insurer's solvency ratio to policyholders, as influenced by different regulatory frameworks (see Section 2.3).

[17]We use the estimated parameter from the system GMM, but the parameter from the fixed effects model is similar.

Figure 3 shows $L_t^p(\xi)$ depending on the reported solvency ratio $SR_{(t-1)^-}$ for the originally calibrated medium reaction parameter ($\xi = 1$), as well as for exemplary higher ($\xi = 3$) and lower ($\xi = 1/3$) reaction parameters. For the reference point of $SR_{t^-} = 225\%$ and higher values, all factors are equal to one. As the solvency ratios decrease, the factors decline exponentially, which is more pronounced for higher reaction parameters owing to the increased curvature. The function is concave up to the cutoff point, beyond which it becomes constant. Consequently, policyholder reactions are present only for life insurers with lower solvency ratios, are more pronounced for those with lower solvency ratios, and stronger for decreases in solvency ratios than for increases. This is in line with our empirical observations in Section 2.2 but is also supported by the experimental findings of Hanika and Gatzert (2024), as well as the regression analyses of Epermanis and Harrington (2006) and Eling and Schmit (2012).

To model policyholders' surrender behavior, we follow Di Francesco and Simonella (2023) and assume that the number of surrendered contracts $c_i(t,\tau)$ for $i \in \{S, R\}$ is binomially distributed. The corresponding probability to surrender a contract which was concluded in year τ at year t is denoted with $\pi(t,\tau)$. Therefore, we accept that the surrender probability is the same for annuities and term life insurance. Moreover, we assume an initial surrender probability π_0 that exponentially decreases with intensity η over the elapsed time $t - \tau$ since the contracts were concluded, because surrender rates in life insurance sharply decline over the first few years (see, e.g., Reck et al., 2023). To model an in- or decrease in policyholders' surrender probability depending on the insurer's reported solvency ratio, we multiply the surrender probability by an additional factor $L_t^c(\xi)$. As before, this factor is calibrated to our regression results from Section 2.2 (see Table A6 in the Appendix) and depends on the reported solvency ratio $SR_{(t-1)^-}$ and the policyholder reaction parameter ξ. As a result, we obtain

$$\pi(t,\tau) = \min\left\{\pi_0 \cdot \exp(-\eta \cdot (t-\tau)) \cdot L_t^c(\xi); 1\right\}$$
$$\text{with } L_t^c(\xi) = \begin{cases} \exp\left(-0.0445 \cdot \xi \cdot \ln\left(\frac{SR_{t-1}}{225\,\%}\right)\right) & \text{if} \quad SR_{t-1} < 225\% \\ 1 & \text{else.} \end{cases} \tag{17}$$

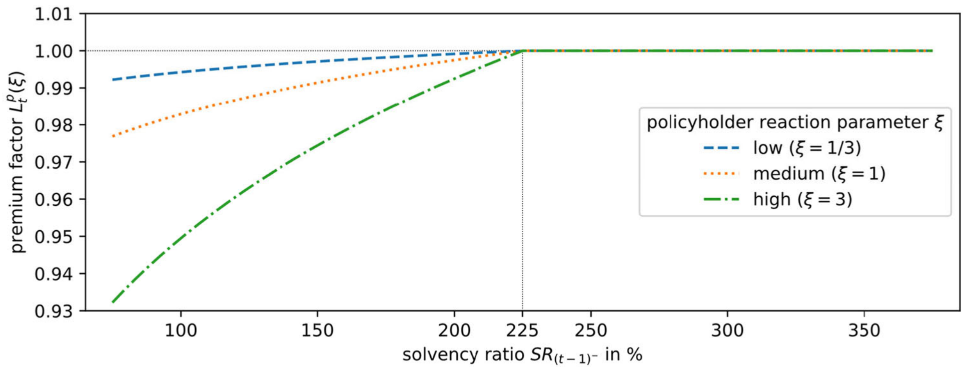

FIGURE 3 Premium factors $L_t^p(\xi)$ depending on the reported solvency ratio $SR_{(t-1)^-}$ for different policyholder reaction parameters ξ.

3.5 | Risk assessment and shareholder value maximization

To assess the life insurer's risk situation, we investigate the default probability over the entire time horizon of T years. Given that the life insurer defaults in year t if adjusted assets $A_{t^-}^{\text{adj}}$ fall below policy reserves PR_{t^-}, let

$$T_s = \inf\left\{t = 1, \ldots, T : A_{t^-}^{\text{adj}} < PR_{t^-}\right\}$$

denote the stopping time of the life insurer's default. Then $PD = P(T_s \leq T)$ defines the default probability and $\overline{PD} = 1/T \cdot PD$ can be interpreted as the average annual default probability (see Gatzert & Wesker, 2012). Additionally, we examine the average solvency ratio over the entire time horizon of T years, that is,

$$\overline{SR} = E\left[\frac{1}{T}\sum_{t=1}^{T} SR_{t^-} \cdot 1\{T_s > t\}\right]. \tag{18}$$

For the life insurer's shareholder value, we assume a perfect capital market with a risk-neutral pricing measure Q.[18] The shareholder value SHV is defined as the expected value under Q of the discounted dividend payments $div(t)$ along with the shareholders' discounted initial contribution E_0 (see Bohnert et al., 2015), that is,

$$SHV = E^Q\Big[\textstyle\sum_{t=1}^{T} \upsilon(1, 1+t) \cdot div(t) \cdot 1\{T_s > t\} + \upsilon(1, 1+T) \cdot \min\{E_0; B_{T^-}\} \cdot 1\{T_s > T\}\Big].$$

Similar to Gründl et al. (2006), we assume that the life insurer maximizes SHV under different management options. While Gründl et al. (2006) consider investment decisions, product portfolio decisions, and initial equity amounts as management options, we focus mainly on the choice of the buffer ratio β, that is,

$$\beta^* = \arg\max\{SHV(\beta) : \beta \in [0, 1]\} \text{ and } SHV^* = \max\{SHV(\beta) : \beta \in [0, 1]\}.$$

This allows us to assess the life insurer's risk-taking behavior: A higher buffer ratio implies a less risky management action, as more of the generated surplus is held as additional reserves to cover unexpected expenses. However, these additional reserves cannot be distributed to shareholders, which generally reduces SHV. Additionally, we consider the choice of asset allocation (i.e., the proportion α of risk-free invested assets) and the product portfolio composition (i.e., the share θ of sold annuities) in the context of sensitivity analyses.

[18] As in Bohnert et al. (2015) or Gründl et al. (2006), we use the risk-neutral pricing measure Q for the life insurer's investments, but the empirical probability measure P for demographic risk. Thus, the investment's drift μ_X in Equation (6) is replaced by the risk-free rate r_t^{SR} to compute the SHV in our simulation analyses (see Bohnert et al., 2015). The discount factors υ are not adjusted, as we assume that the market price of risk is zero (i.e., we set $\lambda = 0$ in Equation (8)).

4 | NUMERICAL ANALYSIS

This section covers the calibration of the model parameters and presents the numerical results. We analyze the impact of market discipline on life insurers' risk-taking behavior depending on the strength of policyholders' reactions, and then perform various sensitivity analyses.

4.1 | Input parameters and simulation methods

We used German mortality data from 1990 to 2020, obtained from the Human Mortality Database, to fit the Lee–Carter model (see Section 3.2). The parameters a_x, b_x, and k_t were estimated using the maximum likelihood method described in Brouhns et al. (2002) and are presented in Figure A2 in the Appendix. The parameter a_x linearly increases with age x, resulting in exponentially higher mortality rates for older individuals (see also Equation (10)). The estimated parameters k_t indicate the general trend toward increased longevity, particularly in age groups around $x = 35$ or $x = 75$ years, given the higher estimated values of b_x. To forecast mortality rates for the years $t > 2020$, we fit a random walk with drift on k_t, yielding a drift of $\phi = -1.1883$ and a volatility of $\sigma_{RW} = 1.9562$ for the Gaussian white noise process ε_t^{RW}. The drift and volatility of the geometric Brownian motion in Equation (6) were estimated using monthly data from the German stock market index DAX spanning October 2008 to October 2023, resulting in $\mu_X = 0.0923$ and $\sigma_X = 0.1834$. For the Vasicek model in Equation (7), we used the parameters $r_1^{SR} = 0.0328$, $\kappa = 0.1129$, $\mu_{SR} = 0.0335$, and $\sigma_{SR} = 0.0085$, which are calibrated on EIOPA's risk-free interest rate term structure curve as of September 2023 for Germany.[19] Simulations of r_t^{SR} for $t > 1$ were drawn from the underlying distribution of the Vasicek model as described in Glasserman (2003). The correlation between the risk-free rate and the risky investment was estimated with monthly DAX data and 1-month EURIBOR rates from October 2008 to October 2023, yielding $\rho = -0.0479$.

The life insurer's asset–liability model accounts for a time horizon of $T = 20$ years. Every year, $n = 5000$ contracts with an actuarial present value of $M = 1000$ are sold.[20] Term life insurance policies (annuities) are bought at the age of $x_S = 35$ ($x_R = 65$) years. We assume a balanced product portfolio with a share of $\theta = 50\%$ annuities and premium loading of $\omega = 15\%$, but both parameters are subject to sensitivity analyses in Section 4.3. Death benefits $S(t)$ and annuities $R(t)$ are calculated according to Equations (12) and (13), with the expected mortality rates from the fitted Lee–Carter model for the years $t \geq 2021$. The discount factors υ are calculated according to Equation (8) based on the fitted Vasicek model. The death counts of policyholders d_S and d_R are drawn from the Poisson distribution given in Equation (11). Similarly, the number of surrendered contracts c_S and c_R is sampled from a binomial distribution with the surrender probability π specified in Equation (17). We assume an initial surrender probability of $\pi_0 = 15\%$ that exponentially decreases with the rate of $\eta = 0.35$, leading to an average annual surrender rate of 2.54% over the entire time horizon of

[19]We employed Equation (8) to minimize the mean squared error between the discount factors under the Vasicek model and those derived under EIOPA's risk-free interest term structure curve for all maturities up to 20 years, using the Nelder–Mead algorithm, assuming $\lambda = 0$.

[20]In contrast to the run-off setting in Gatzert and Wesker (2012), where 100,000 contracts with $M = 1000$ are sold once at the beginning, we use 5000 contracts with $M = 1000$ sold annually over 20 years.

20 years.[21] The surrender fee c is accepted to be zero. For shareholders' initial equity, we use $E_0 = 20{,}000$, which results in the initially expected solvency ratio $SR_{0^-} = 225\%$. The proportion α invested at the risk-free rate is set to 85% but is subject to sensitivity analyses in Section 4.3.

In the following sections, all numerical results are derived from quasi-Monte Carlo simulations with $2^{16} = 65{,}536$ Sobol sequences using the method of inverse transformation (see Glasserman, 2003). To ensure comparability between different results, the same Sobol sequences are used for all simulations. The buffer ratios β^* that maximize SHV are found by a line search with step width $\Delta\beta = 0.01$.[22]

4.2 | Impact of market discipline on life insurers' risk-taking behavior

First, we investigate the impact of public risk disclosure on life insurers' risk-taking behavior by comparing two scenarios: In scenario 1 (no market discipline), policyholders do not adjust their willingness to pay and surrender behavior, regardless of the life insurer's reported solvency ratio (i.e., we set $\xi = 0$ in Equations (16) and (17)). In scenario 2 (market discipline), policyholders adjust their willingness to pay and surrender behavior depending on the life insurer's solvency ratio, as observed in the German life insurance market ($\xi = 1$). For both scenarios, Figure 4 shows the average solvency ratio $\overline{SR}$, average annual default probability $\overline{DP}$, and shareholder value SHV, respectively, for different buffer ratios β.

Because β describes the fraction of the life insurer's generated surplus, which is held as additional capital reserves rather than distributed to shareholders, $\overline{SR}$ increases for higher buffer ratios β (see Figure 4a) and $\overline{DP}$ decreases (see Figure 4b). The shareholder value SHV is the smallest for $\beta = 1$, in which case all the surplus is held as reserves and none is distributed to shareholders (see Figure 4c). Decreasing β first sharply increases SHV and then steadily decreases SHV, as higher default probabilities eventually outweigh greater participation in the life insurer's surplus. Comparing the scenarios with and without market discipline (dotted vs. dashed lines), Figure 4a shows only small differences in $\overline{SR}$. For $\beta \leq 0.85$, $\overline{SR}$ is slightly lower in the case of market discipline, as the solvency ratios lie below the reference point of 225% and policyholders pay less.

The differences in $\overline{DP}$ are more pronounced (see Figure 4b). In both cases, $\overline{DP}$ is approximately zero for all $\beta \geq 0.85$. Reducing β from this point leads to a linear increase in $\overline{DP}$ by up to 3% for $\beta = 0$ in the absence of market discipline. If market discipline exists, the policyholders' reduced willingness to pay and increased surrender probability enhance the increase in $\overline{DP}$. Therefore, the increase is steeper and saturates at $\overline{DP} = 5\%$, implying a certain default for the 20-year time horizon. Similarly, SHV is approximately equal in both scenarios for $\beta \geq 0.85$, but the maximum is reached at a larger buffer ratio β in the case of market discipline and declines faster afterward compared to the case of no market discipline.

[21]According to the German Insurance Association, the surrender rate for life insurance products decreased from 2.57% in 2021 to 2.52% in 2022 (see www.gdv.de).

[22]No constraints were enforced to ensure that the life insurer's reported solvency ratio remained above the regulatory required level of 100%. This approach allows us to interpret the results in the following sections as if no capital requirements exist and to analyze whether market discipline can compensate for this. However, we also briefly discuss the impact of a regulatory solvency ratio of 100% in Section 4.2.

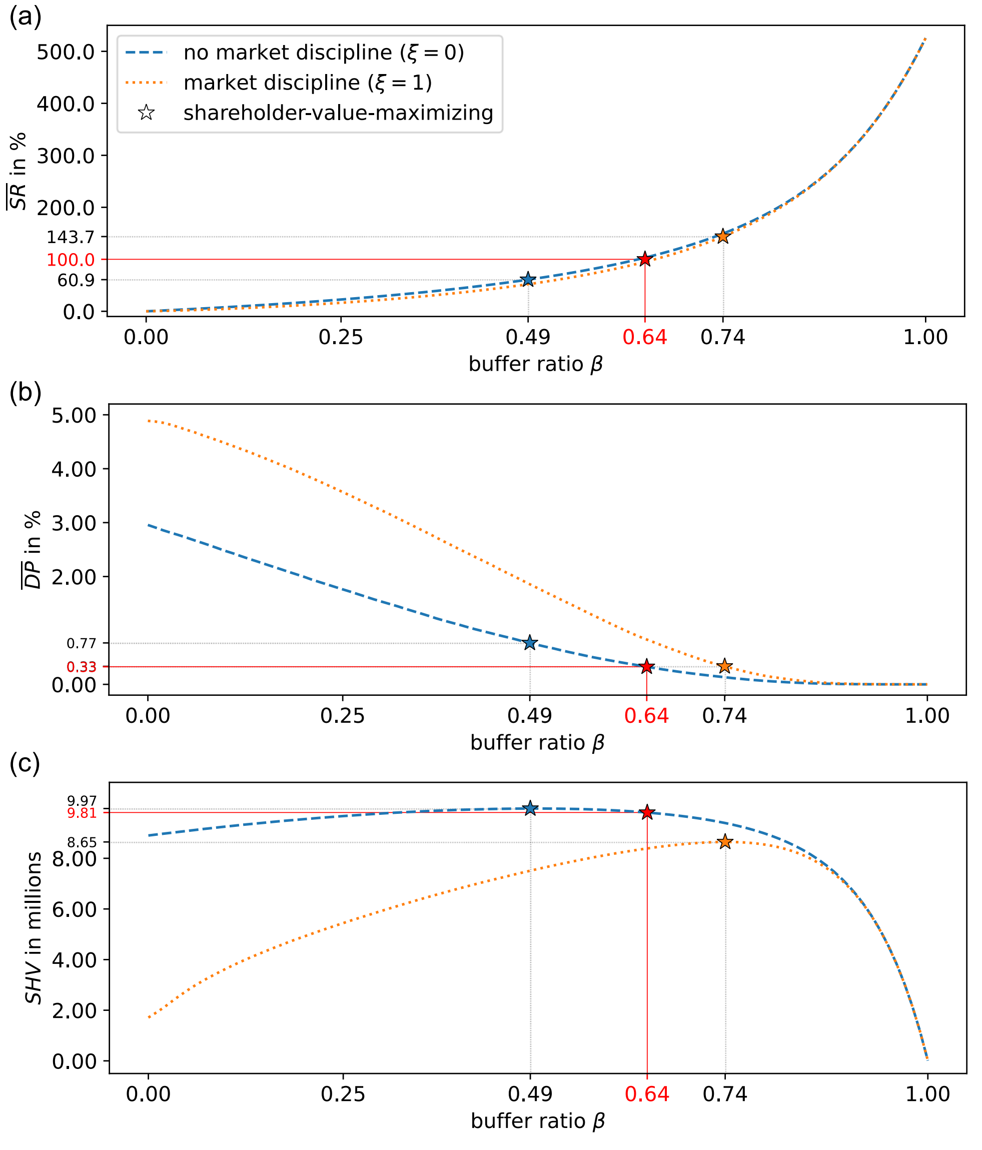

FIGURE 4 Average solvency ratio $\overline{SR}$ (a), average annual default probability $\overline{DP}$ (b), and shareholder value SHV (c) for different buffer ratios β with and without market discipline. In the case of "no market discipline," policyholders do not adjust their willingness to pay and surrender behavior regardless of the life insurer's reported solvency ratio. In the case of "market discipline," policyholders adjust their willingness to pay and surrender behavior depending on the life insurer's reported solvency ratio according to Equations (16) and (17) with $\xi = 1$. The solid horizontal and vertical lines show the values under the regulatory required solvency ratio of 100% for $\xi = 0$.

Neglecting any regulatory capital requirements, the higher shareholder-value-maximizing buffer ratio of $\beta^* = 0.74$ compared to $\beta^* = 0.49$ in Figure 4c shows that the life insurer acts less riskily in our model (i.e., holds more reserves) if market discipline exists. Furthermore, we observe a higher average solvency ratio of $\overline{SR} = 143.7\%$ and a lower average annual default probability of $\overline{DP} = 0.33\%$ at $\beta^* = 0.74$ compared to $\overline{SR} = 60.9\%$ and $\overline{DP} = 0.77\%$ at $\beta^* = 0.49$. Therefore, policyholders' behavior reduces the life insurer's risk-taking in our model, which is in line with previous research (see Gründl et al., 2006; Nirmalendran et al., 2013). We observe a substantial decrease (−57.1%) in the life insurer default probability and an improvement in the average solvency ratio of 136.0% at the cost of a reduction in SHV^* from 9.97 to 8.65 million (−13.2%). The average solvency ratio of $\overline{SR} = 143.7\%$ is above the required level of 100% under Solvency II, and the annual default probability of $\overline{DP} = 0.33\%$ is below the Solvency II target value of 0.50%. These findings indicate that market discipline can compensate for missing regulatory capital requirements in our model. This finding is similar to that of Nirmalendran et al. (2013), who also find that life insurers should target annual default probabilities below 0.5%.

As the solvency ratio of $\overline{SR} = 60.9\%$ would not be allowed under Solvency II, the solid horizontal and vertical lines in Figure 4 show the shareholder-value-maximizing values in the case of no market discipline that would ensure the solvency ratio of $\overline{SR} = 100\%$. This would require more reserves to be held (i.e., the buffer ratio increases from $\beta^* = 0.49$ to $\beta^* = 0.64$) (see Figure 4a). Although the higher buffer ratio and the regulatory required solvency ratio still lie below the values of $\beta^* = 0.74$ and $\overline{SR} = 143.7\%$ in the case of market discipline, the same average annual default probability of $\overline{DP} = 0.33\%$ can be seen in Figure 4b. Consequently, capital requirements appear to reduce a life insurer's risk situation as effectively as market discipline in our model. However, this result holds only for $\xi = 0$ (i.e., if policyholders show no reaction to a life insurer's risk level). Even if no public reporting requirements exist, one could assume a low policyholder reaction parameter ξ because of rating agencies and financial advisors.

To investigate the significance of the strength of policyholders' reactions (e.g., caused by more or less disclosure), Figure 5 shows the average annual default probability $\overline{DP}$, average solvency ratio $\overline{SR}$, and shareholder value SHV depending on the buffer ratio β for the originally calibrated policyholder reaction parameter ($\xi = 1$), as well as for the higher ($\xi = 3$) and lower ($\xi = 1/3$) parameters. For the higher parameter (dash-dotted line), policyholders' asymmetric behavior becomes more visible in Figure 5a: higher buffer ratios with average solvency ratios above the reference point of $\overline{SR} = 225\%$ yield the same values as the medium or lower parameter, but the reduction for lower buffer ratios with average solvency ratios below the reference point is clearly more pronounced. Because higher values of ξ enhance policyholders' reactions in terms of willingness to pay and surrender behavior, $\overline{DP}$ (SHV) increases (decreases) earlier and steeper for higher values of ξ when β is reduced.

Considering the shareholder-value-maximizing values in Figure 5c, the optimal buffer ratio β^* increases for progressively higher parameters of $\xi = 1/3$, $\xi = 1$, and $\xi = 3$. As in Figure 4, these higher optimal buffer ratios result in higher average solvency ratios $\overline{SR}$ (see Figure 5a), lower average annual default probabilities $\overline{DP}$ (see Figure 5b), and lower optimal shareholder values SHV^* (see Figure 5c). For example, $\overline{DP}$ progressively decreases from 0.49% to 0.33% to 0.30% and SHV^* from 9.37 to 8.65 to 7.65 million. However, the stepwise reduction in $\overline{DP}$ (0.16 vs. 0.03 percentage points) decreases, whereas the stepwise reduction in SHV^* (0.72 vs. 1.00 million) increases. This shows that increasing the strength of policyholders' reactions becomes progressively costlier and less effective in further reducing the life insurer's default risk in our simulation analysis. Moreover, this seems to contradict the accelerated increase in $\overline{SR}$ from 97.0% to 143.7% to 209.8%.

To explain this observation, Figure 6 shows the distribution of the average solvency ratios rather than the expected values given in Equation (18). The higher policyholder reaction

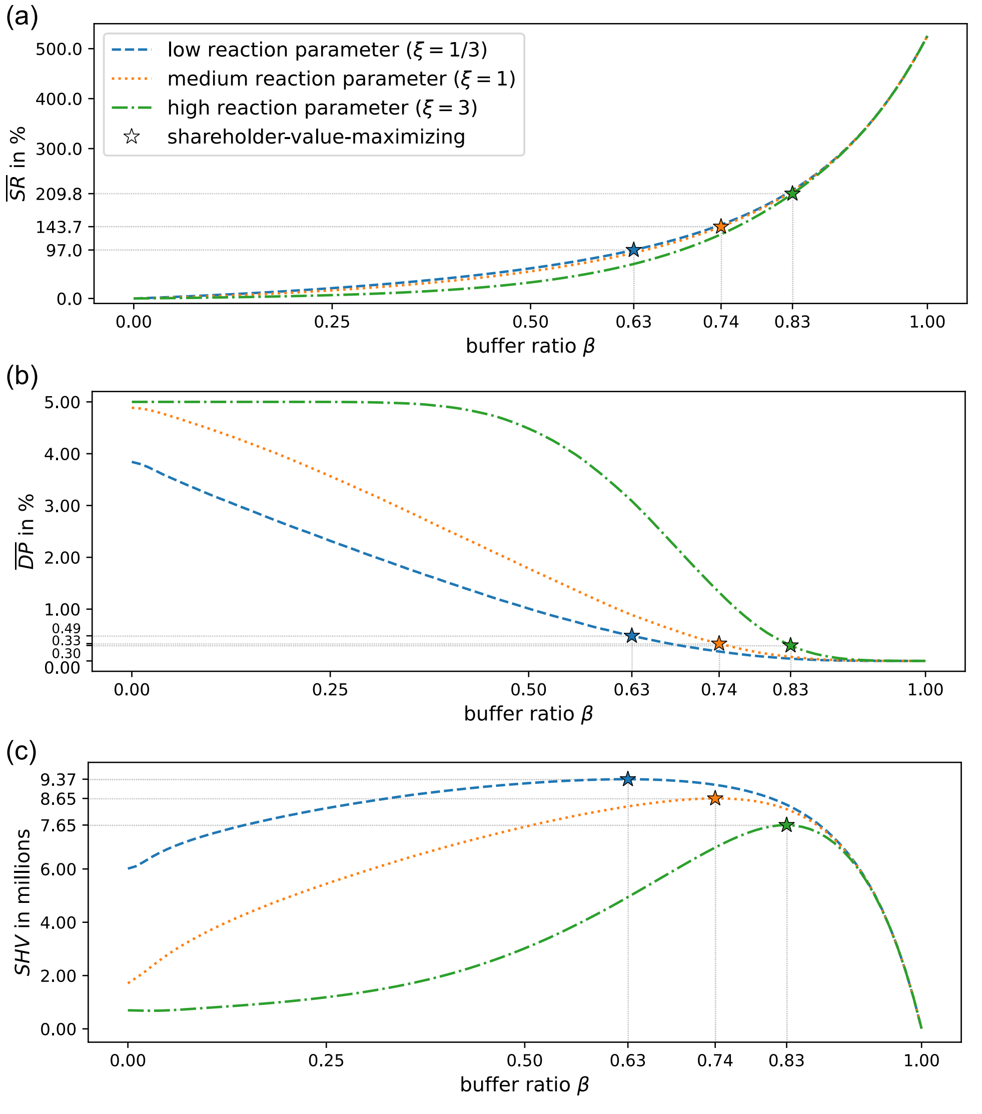

FIGURE 5 Average solvency ratio $\overline{SR}$ (a), average annual default probability $\overline{DP}$ (b), and shareholder value *SHV* (c) for different buffer ratios β and policyholder reaction parameters ξ.

parameter ξ moves the distributions to the right (which explains the higher expected values shown in Figure 5), but the variances also increase. The left tails of the distributions, where the solvency ratios are small, are most relevant to the life insurer's risk situation (e.g., for the default probability). Therefore, the positive effects of higher expected values are partially negated by the more pronounced left tails owing to the increased variances. This effect is further enhanced as the distributions are left-skewed, whereby the most pronounced left tail can be observed for the highest reaction parameter (dash-dotted line). An economic explanation for this observation is that our model framework does not consider reactive management actions. Therefore, policyholders' more pronounced reactions (i.e., their reduced willingness to

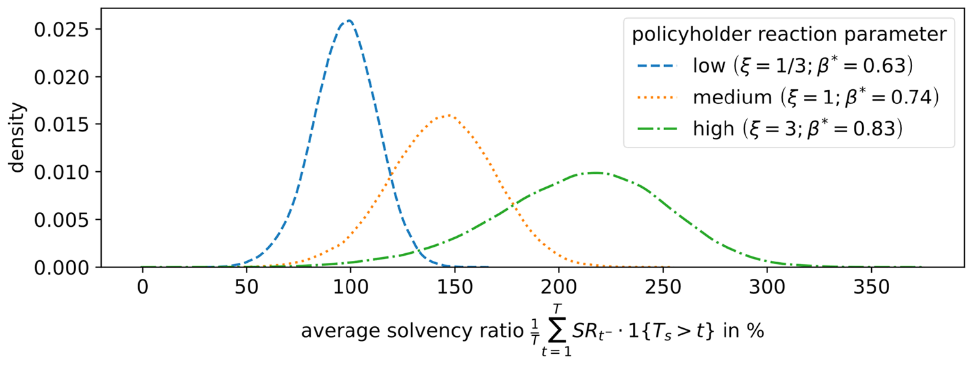

FIGURE 6 Kernel density plots of the shareholder-value-maximizing average solvency ratios for different policyholder reaction parameters ξ.

pay and increased surrender probability) make it difficult for life insurers whose solvency ratios have dropped to recover financially. Consequently, policyholders are more likely to drive troubled life insurers toward insolvency in our model. This is similar to the effect of depositor behavior during bank runs.

Several policy implications can be drawn from our simulation analysis. The finding that policyholders' reactions to changes in publicly reported solvency ratios can influence a life insurer's management decisions and reduce default risk supports the value of public risk disclosure requirements, as mandated by Solvency II. Stronger policyholder reactions enhance the reduction in the default probability, suggesting that lowering search costs for policyholders and raising public awareness of an insurer's solvency ratio could be beneficial. However, in our model, the effectiveness of intensifying policyholder reactions diminishes over time and becomes increasingly expensive. Therefore, the costs and benefits of improving market discipline through more public disclosure should be evaluated carefully.

Another problem arises when solvency ratios can be manipulated by specific management actions that do not accurately reflect the insurer's actual risk exposure. For example, Grochola and Schlütter (2025) show that discretionary decisions regarding the use of long-term guarantee measures strongly influence Solvency II capital requirements and are particularly employed by insurers with low solvency ratios. Not directly related to Solvency II, Koijen and Yogo (2015) found that U.S. life insurers reacted to balance sheet shocks during the 2008 financial crisis by selling policies far below actuarial value to increase statutory capital. Lu et al. (2017) observe that life insurers' decisions to sell downgraded bonds are strongly driven by the RBC formula (e.g., NAIC rating categories and risk factors) rather than changes in risk exposure. Strengthening market discipline may worsen these issues by encouraging the management to focus on improving solvency ratios in ways that do not reflect the underlying risks. Policymakers should be mindful of these potentially unintended consequences.

4.3 | Sensitivity analysis

In this section, we conduct multiple sensitivity analyses to investigate the robustness of our results for different premium loadings, product portfolio compositions, and asset allocations.

4.3.1 | Role of premium loadings

Because policyholders' risk-sensitive willingness to pay is modeled by an additional premium factor (see Equation (16)), interaction effects with the premium loading ω in Equations (12) and (13) may exist. To test the robustness of the results in the previous section, we perform a sensitivity analysis for the premium loading ω. Figure 7 shows the buffer ratios β^* that maximize SHV along with the optimal shareholder values SHV^*, average annual default probabilities $\overline{DP}$, and average solvency ratios $\overline{SR}$ for different premium loadings ω and different policyholder reaction parameters ξ.

As a first result, higher premium loadings ω (i.e., higher premium income) decrease $\overline{DP}$ (see Figure 7a) and β^* (see Figure 7c) but increase $\overline{SR}$ (see Figure 7b) and SHV^* (see Figure 7d), regardless of the policyholder reaction parameter ξ. The only exception is that for $\xi = 0$, the average solvency ratios $\overline{SR}$ are approximately equal for all premium loadings ω. In line with the results from Section 4.2, more reserves are held (i.e., higher buffer ratios β^* are chosen) for

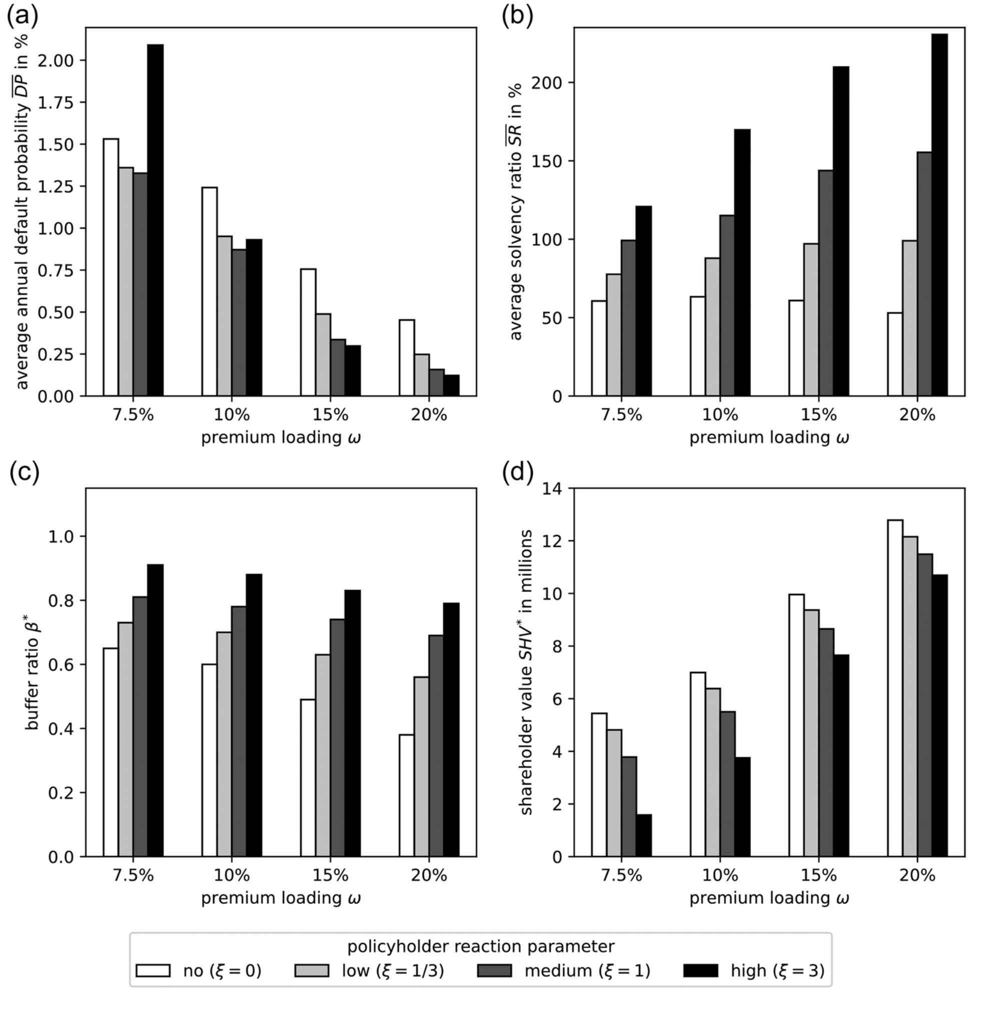

FIGURE 7 Shareholder-value-maximizing values for different levels of policyholder risk sensitivity ξ and premium loadings ω.

higher values of ξ, which reduces the shareholder value SHV^*. Furthermore, for all premium loadings $\omega \geq 15\%$, these higher buffer ratios improve the life insurer's risk situation owing to the lower average annual default probabilities $\overline{DP}$ and higher average solvency ratios $\overline{SR}$. The risk reduction, compared to the case of no market discipline, becomes more pronounced for higher premium loadings (see Figure 7a,b). For the lowest premium loadings of $\omega = 7.5\%$ and $\omega = 10\%$, where the life insurer faces higher risks, the lowest average annual default probability $\overline{DP}$ is observed for medium risk sensitivity $\xi = 1$ rather than for the largest risk sensitivity of $\xi = 3$.

These observations suggest that public risk disclosure may be more effective in promoting less risky management actions in business lines with higher loadings (i.e., higher profit margins). In such cases, insurers can charge higher premiums, and a decline in policyholders' willingness to pay has a more significant impact. However, the results also indicate that stronger policyholder reactions do not always reduce risk. In fact, when premium loadings are small, more pronounced reactions could even increase the life insurer's risk exposure in our model. Therefore, our simulation suggests that strengthening public risk disclosure requirements in highly competitive markets—where insurers have limited flexibility—could create more problems than benefits.

4.3.2 | Choice of product portfolio composition and asset allocation

To investigate the impact of market discipline on a life insurer's choice of product portfolio composition, Figure 8 presents the buffer ratios β^* that maximize SHV, along with the optimal shareholder values SHV^*, average annual default probabilities $\overline{DP}$, and average solvency ratios $\overline{SR}$. These are shown for different product portfolio compositions θ and for the policyholder reaction parameters $\xi = 0$ (no market discipline) and $\xi = 1$ (market discipline).

When comparing the dashed and dotted lines in Figure 8, higher buffer ratios β^* are chosen if market discipline exists, which also improves the life insurer's risk situation (i.e., $\overline{SR}$ increases and $\overline{DP}$ decreases) at the expense of lower shareholder values SHV^*. These observations are consistent with the findings presented in Section 4.2. For $\xi = 0$, the buffer ratio β^* increases linearly as the share of sold annuities increases (see Figure 8c), whereas SHV^* decreases linearly from its highest value of $SHV^* = 10.48$ million at $\theta = 0.0$ (see Figure 8d). For $\xi = 1$, the buffer ratios β^* are approximately equal for all product portfolio compositions, while SHV^* first increases until the maximum $SHV^* = 8.67$ million is reached at $\theta = 0.6$ and then decreases for higher values of θ. Furthermore, Figure 8a shows that selling mixed portfolios consisting of annuities and term life insurance policies reduces the life insurer's average annual default probability $\overline{DP}$ compared to a situation in which only term life insurance policies (i.e., $\theta = 0$) or annuities (i.e., $\theta = 1$) are sold. This observation can be explained by the opposing effects of mortality changes on the two product types, which is in line with previous studies on natural hedging in life insurance (see Gatzert & Wesker, 2012). Thus, market discipline fosters less risky management actions by the life insurer, not only because more reserves are held but also because a more balanced and less risky product portfolio composition is chosen.

Figure 9 shows the shareholder-value-maximizing values for $\xi = 0$ (no market discipline) and $\xi = 1$ (market discipline), depending on the proportion α of assets invested risk-free. Higher buffer ratios β^* are chosen if market discipline exists, which increases $\overline{SR}$ and generally decreases $\overline{DP}$ and SHV^* (see dashed vs. dotted lines). Given that a higher proportion of assets invested risk-free (i.e., a lower amount invested in stocks) generally improves the risk situation

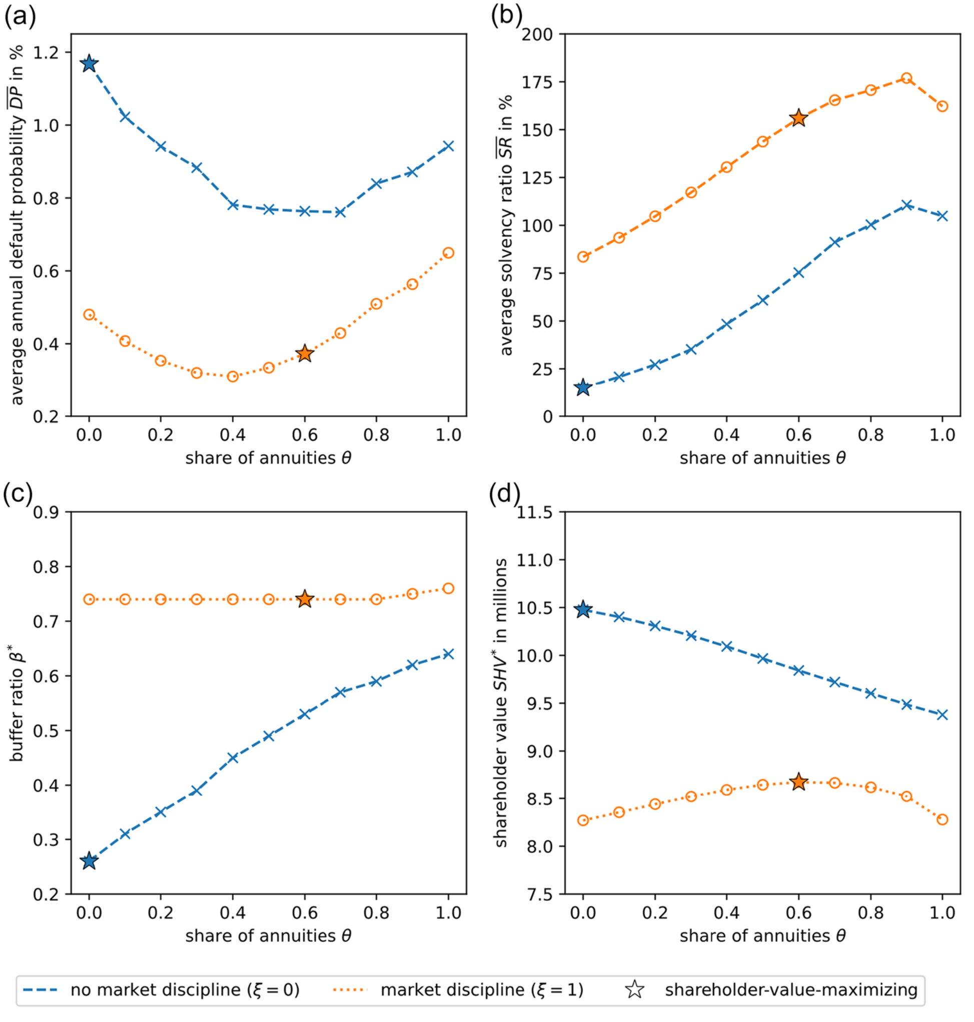

FIGURE 8 Shareholder-value-maximizing values for different product portfolio compositions θ in the cases of no market discipline ($\xi = 0$) and market discipline ($\xi = 1$).

of the life insurer, $\overline{DP}$ decreases for higher values of α (see Figure 9a). Only at very high values of $\alpha = 0.8$ (no market discipline) or $\alpha = 0.9$ (market discipline) do diversification effects arise, with $\overline{DP}$ increasing afterward. This can be explained by (1) the slightly negative correlation between the risky and the risk-free investment (see Section 4.1) and (2) the decline in buffer ratios β^* for higher values of α. The latter is particularly pronounced in the case of no market discipline (see Figure 9c). Similarly, $\overline{SR}$ initially increases for higher values of α because the risk-based Solvency II standard formula charges higher SCRs for stock investments (see Figure 9b). However, at some point, the lower buffer ratios β^* (i.e., the lower reserves) outweigh the positive effects and $\overline{SR}$ begins to decline. Since the decreasing buffer ratios β^* for higher values of α imply that more of the life insurer's surplus is distributed to shareholders as dividends, SHV^* increases. This is observed for $\xi = 0$ and $\xi = 1$. Thus, in both cases (with and without market discipline), the life insurer prefers to invest all assets at the risk-free rate to obtain the possibility of higher dividend payments.

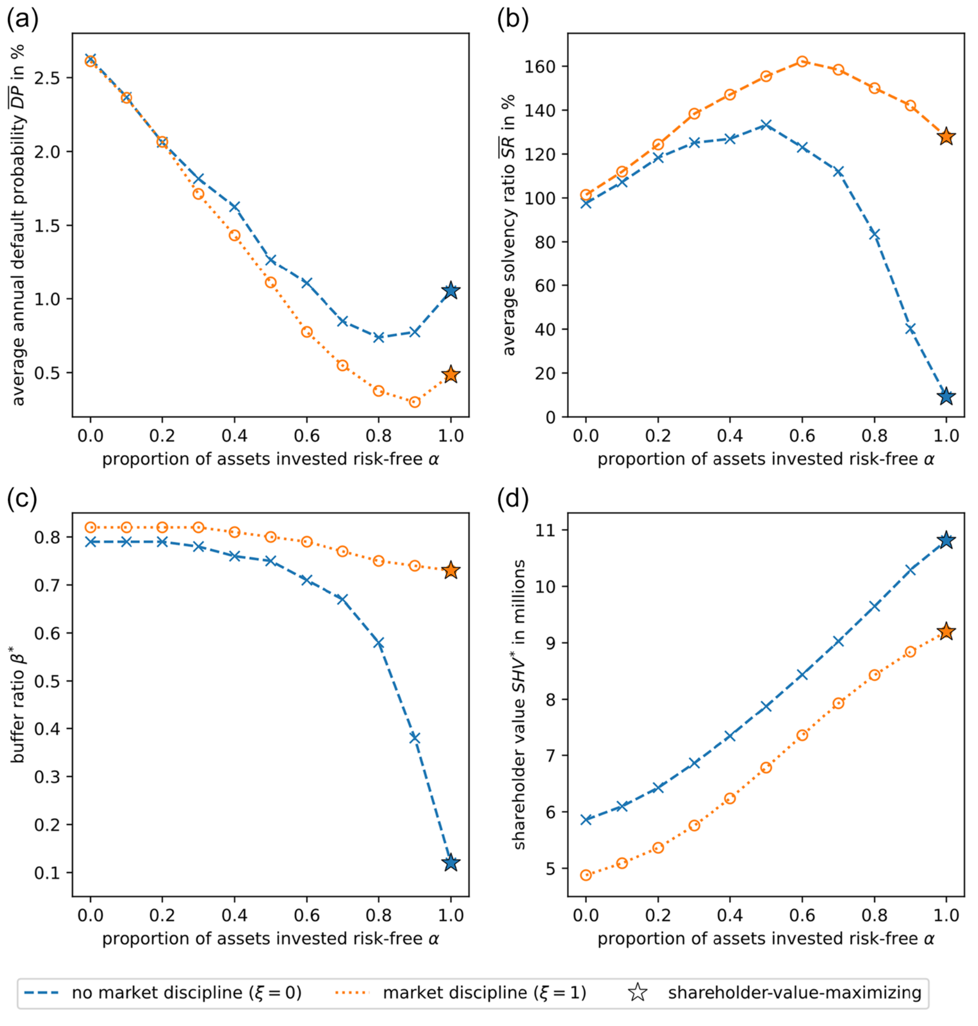

FIGURE 9 Shareholder-value-maximizing values for different asset allocations α in the cases of no market discipline ($\xi = 0$) and market discipline ($\xi = 1$).

5 | SUMMARY

This study investigates whether public risk disclosure, specifically Solvency II, can encourage less risky management actions among life insurers. First, we employ static and dynamic panel regressions, drawing on data from 58 German life insurers between 2016 and 2023, to provide empirical evidence on customer-driven market discipline. Consistent with prior research on the impact of insurer rating changes, we find that policyholders adjust their purchase and surrender behavior in response to changes in publicly disclosed solvency ratios. Moreover, our results suggest that life insurers reduce their risk exposure when facing a decline in their solvency ratio, as evidenced by a more pronounced increase in their solvency ratio the following year. These effects are more pronounced (or only observed) among life insurers with lower solvency ratios.

Building on these findings, we develop a shareholder value maximization model to examine whether policyholder behavior—specifically their reduced willingness to pay and increased probability of surrendering policies—can explain the observed reduction in risk-taking by life insurers. This study extends the existing literature on market discipline in life insurance, which relies on run-off models calibrated on experiments or theoretical assumptions to analyze the impact of insolvency-averse policyholders on life insurers' decision-making. In contrast, we use a multi-period asset–liability model aligned with the Solvency II framework and calibrated to our empirical observations from the German market. In our model, the life insurer *annually* discloses its solvency ratio to the public, thereby *dynamically* influencing policyholders' willingness to pay for new policies and their surrender behavior for existing contracts. The model accounts for stochastic mortality rates, risk-free and risky investments, two lines of business (annuity and term life), fairly priced premiums with additional loadings, and annual dividend payments to shareholders. Solvency ratios are calculated using a simplified Solvency II standard formula. We employ quasi-Monte Carlo methods to calculate the life insurer's default probabilities, average solvency ratios, and shareholder values under different levels of policyholder reactions. To assess the insurer's risk-taking behavior, we examine the level of reserves that maximizes shareholder value, as well as the choice of product portfolio composition and asset allocation through sensitivity analyses.

Our simulation analyses indicate that insolvency-averse policyholders can encourage less risky management actions by life insurers. When solvency ratios are disclosed and policyholders react to them, the life insurer holds more reserves to maximize shareholder value, thereby reducing the default probability. Stronger policyholder reactions yield higher reserves, though the reduction in default probability becomes progressively smaller and more costly. Additionally, we find positive effects on product portfolio composition: the life insurer selects a more balanced and less risky portfolio in the presence of market discipline. Finally, our simulation suggests that public risk disclosure may be more effective in reducing default risk when product profit margins are sufficiently high. In highly competitive markets, characterized by low premium loadings, stronger policyholder reactions may even increase default risk, according to our model.

These findings offer valuable insights into the potential benefits and limitations of public risk disclosure, which are relevant for both regulators and insurers. Life insurers should consider policyholders' reactions to disclosed solvency ratios, particularly in high-profit lines of business, to maximize shareholder value. Public disclosures could foster less risky management decisions and complement regulatory oversight—provided that disclosures are understandable for policyholders and solvency ratios accurately reflect risk. Finding the right level and design of public risk disclosure seems important to avoid undue costs or unintended consequences. Therefore, systematic cost-benefit analyses of the increasing disclosure requirements under Solvency II are warranted. A limitation of this paper is that, despite being calibrated on real market data, our theoretical model relies on simplifications and assumptions. Further research could enhance the credibility of the results by conducting external validations, for example, by analyzing how differences in regulatory reporting regimes influence the effectiveness of market discipline.

ACKNOWLEDGMENTS

The author would like to thank Randy Dumm, Cameron Ellis, Nadine Gatzert, Kenny Wunder, the participants at the Annual Conference of the German Association for Insurance Science 2024 in Berlin, the Annual Meeting of the American Risk and Insurance Association 2024 in

Denver, and the Annual Seminar of the European Group of Risk and Insurance Economists 2024 in Hamburg, as well as the anonymous reviewers and the editor for their valuable comments on an earlier version of this paper. Open Access funding enabled and organized by Projekt DEAL.

CONFLICT OF INTEREST STATEMENT

The author declares no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data and source code of this study are available in the online repository of the Journal of Risk and Insurance.

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How to cite this article: Hanika, M. (2025). Market discipline in life insurance: Does public risk disclosure encourage less risky management actions? *Journal of Risk and Insurance*, *92*, 909–949. https://doi.org/10.1111/jori.70019

APPENDIX A

TABLE A1 Increase or decrease in the term structure of interest rates according to the Solvency II interest risk sub-module defined in the Commission Delegated Regulation (EU) 2015/35.

Maturity (in years)	Increase	Decrease
1	70%	75%
2	70%	65%
3	64%	56%
4	59%	50%
5	55%	46%
6	52%	42%
7	49%	39%
8	47%	36%
9	44%	33%
10	42%	31%
11	39%	30%
12	37%	29%
13	35%	28%
14	34%	28%
15	33%	27%
16	31%	28%
17	30%	28%
18	29%	28%
19	27%	29%
20	26%	29%

TABLE A2 Summary statistics for the regression sample in comparison with the full market of all German life insurers between 2016 and 2023.

Year	2016	2017	2018	2019	2020	2021	2022	2023
Full market								
Number of companies	87	87	87	85	83	82	82	84
Gross written premiums (bn €)	86.17	86.11	88.32	98.32	98.65	98.34	91.43	87.75
Median surrender rate (%)	3.2	3.1	3.1	3.2	3.3	3.2	3.1	3.4
Median costs (%)	10.2	10.3	10.5	10.7	10.9	10.4	11.8	12.2
Assets under management (bn €)	985.69	1020.58	1038.83	1099.59	1142.62	1209.85	1196.82	1210.83
Total sum insured (bn €)	3004.29	3094.22	3125.95	3216.50	3323.29	3465.23	3548.85	3629.63
Regression sample								
Number of companies	58	58	58	58	58	58	58	58
Gross written premiums (bn €)	73.11	73.43	75.80	85.93	86.14	85.32	79.50	74.70
Median surrender rate (%)	3.3	3.2	3.2	3.2	3.3	3.2	3.3	3.5
Median costs (%)	10.4	10.5	11.1	11.4	11.4	11.5	12.3	13.55
Assets under management (bn €)	823.10	851.22	859.55	929.17	969.38	1030.27	1024.17	999.77
Total sum insured (bn €)	2505.68	2599.12	2633.63	2747.91	2854.06	3003.01	3085.73	3123.08

Note: The surrender rate includes early terminations, surrenders, and conversions to paid-up policies (expressed as a percentage of the sum insured within the insurer's portfolio). The costs are composed of acquisition and running costs (measured as a percentage of gross written premiums). For annuities, the sum insured is calculated as 12 times the annual annuity.

TABLE A3 Correlation matrix and variance inflation factors (VIF) for all variables used in the regression models (R1) and (R2).

Variables	$\Delta P_{i,t}$	$\Delta\Pi_{i,t}$	$P^*_{i,t}$	$\Delta\text{Costs}_{i,t}$	$\Delta SR_{i,t-1}$
$\Delta P_{i,t}$	1.0000				
$\Delta\Pi_{i,t}$	−0.1248**	1.0000			
$P^*_{i,t}$	0.0349	−0.0161	1.0000		
$\Delta\text{Costs}_{i,t}$	0.0251	0.0419	0.0086	1.0000	
$\Delta SR_{i,t-1}$	−0.1116**	0.0539	−0.0865	0.0312	1.0000
VIF			5.1921	1.0325	1.4636

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Year dummies are included to calculate VIF, but not displayed.

TABLE A4 Correlation matrix and variance inflation factors (VIF) for all variables used in the regression model (R3).

Variables	$\Delta SR_{i,t}$	$P^*_{i,t}$	$\Delta \text{Costs}_{i,t}$	$\Delta SR^{down}_{i,t-1}$
$\Delta SR_{i,t}$	1.0000			
$P^*_{i,t}$	−0.0283	1.0000		
$\Delta \text{Costs}_{i,t}$	0.0561	0.0086	1.0000	
$\Delta SR^{\text{down}}_{i,t-1}$	0.2542***	0.0037	−0.0413	1.0000
VIF		5.1823	1.0263	1.6409

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Year dummies are included to calculate VIF, but not displayed.

TABLE A5 Descriptive statistics for all variables used in models (R1–R3).

Variable	Mean	Median	Std.	Min.	Max.
$\Delta P_{i,t}$	0.0033	0.0115	0.1251	−0.5577	0.8193
$\Delta \Pi_{i,t}$	0.0046	0.0000	0.1584	−0.9651	0.6493
$\Delta SR_{i,t}$	0.0341	0.0297	0.4101	−1.9994	1.8171
$P^*_{i,t}$	6.3908	6.4505	1.2231	3.8918	10.2656
$\Delta \text{Costs}_{i,t}$	0.0133	0.0162	0.1219	−0.8348	0.7355
$\Delta SR_{i,t-1}$	0.1007	0.0651	0.4703	−1.9994	3.434
$\Delta SR^{\text{down}}_{i,t-1}$	0.1143	0.0000	0.2372	0.0000	1.9994

Note: The variable $\Delta P_{i,t}$ defines the log premium growth, $\Delta \Pi_{i,t}$ the log change in surrender rate, $\Delta SR_{i,t}$ is the log change in solvency ratio, $\Delta Costs_{i,t}$ is the log change in costs, $\Delta SR^{\text{down}}_{i,t}$ is the log decrease in solvency ratio, and $P^*_{i,t}$ represents the log written premiums in million Euros.

TABLE A6 Results of model (R2) with the log change in surrender rate as the dependent variable.

	Fixed effects		System GMM	
Variables	Variant 1	Variant 2	Variant 1	Variant 2
$P^*_{i,t}$	0.0601 (0.1053)	0.0615 (0.1056)	0.0029 (0.0056)	0.0017 (0.0050)
$\Delta Costs_{i,t}$	0.1380 (0.1349)	0.1379 (0.1353)	0.0941 (0.1158)	0.0543 (0.0899)
$\Delta SR_{i,t-1}$	−0.0325 (0.0214)		−0.0365** (0.0170)	
$\Delta SR_{i,t-1} \times Lower^{50\%}_{i,t-1}$		−0.0373 (0.0239)		−0.0445*** (0.0150)
$\Delta SR_{i,t-1} \times Upper^{50\%}_{i,t-1}$		−0.0156 (0.0272)		0.0073 (0.0178)
$\Delta P_{i,t-1}$			−0.1616* (0.0977)	−0.1572* (0.0953)

(Continues)

TABLE A6 (Continued)

Variables	Fixed effects Variant 1	Fixed effects Variant 2	System GMM Variant 1	System GMM Variant 2
$\Delta\Pi_{i,t-1}$			−0.2012*** (0.0691)	−0.2003*** (0.0732)
R^2 (within)	0.1012	0.1020		
Sargan–Hansen test (*p*-value)			0.7136	0.9213
Arellano–Bond test AR(1) (p-value)			0.0159	0.0248
Arellano–Bond test AR(2) (*p*-value)			0.9434	0.9969
Num firms			58	
Num observations			348	

Note: The table shows estimated coefficients and robust standard errors (clustered at the firm level) in brackets. Year dummies are included, but not reported. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The variable $\Delta Costs_{i,t}$ defines the log change in costs, $\Delta SR_{i,t-1}$ is the log change in solvency ratio, $\Delta\Pi_{i,t-1}$ is the log change in surrender rates, $\Delta P_{i,t-1}$ represents the log premium growth, and $P^*_{i,t}$ the log premiums. The dummy variables $Upper^{50\%}_{i,t-1}$ and $Lower^{50\%}_{i,t-1}$ take one if the solvency ratio is among the 50% highest or lowest of all solvency ratios, respectively.

TABLE A7 Results of model (R3) with log change or log increase (rather than log decrease) in the solvency ratio.

Variables	Fixed effects Variant 1	Fixed effects Variant 2	System GMM Variant 1	System GMM Variant 2
$P^*_{i,t}$	−0.3033*** (0.1037)	−0.3052*** (0.1039)	−0.0134 (0.0104)	−0.0077 (0.0107)
$\Delta Costs_{i,t}$	−0.2261 (0.2096)	−0.2295 (0.2011)	−0.0935 (0.2303)	−0.1575 (0.2391)
$\Delta SR_{i,t-1}$	−0.1096* (0.0587)		−0.0449 (0.0499)	
$\Delta SR^{up}_{i,t-1}$		0.0499 (0.0972)		0.1170 (0.0934)
$\Delta P_{i,t-1}$			−0.0255 (0.2997)	−0.0340 (0.3129)
R^2 (within)	0.3473	0.3383		
Sargan–Hansen test (*p*-value)			0.1732	0.1329
Arellano–Bond test AR(1) (*p*-value)			<0.0001	0.0005
Arellano–Bond test AR(2) (*p*-value)			0.0652	0.0829
Number of firms		58		
Number of observations		348		

Note: The table shows estimated coefficients and robust standard errors (clustered at the firm level) in brackets. Year dummies are included, but not reported. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The variable $\Delta Costs_{i,t}$ defines the log change in costs, $\Delta P_{i,t-1}$ is the log premium growth, $SR_{i,t-1}$ is the log change in solvency ratio, $SR^{up}_{i,t-1}$ is the log increase in solvency ratio, and $P^*_{i,t}$ represents the log premiums.

TABLE A8 Robustness tests for the results of model (R3) with the log change in solvency ratio as the dependent variable.

	Fixed effects		System GMM	
Variables	**Variant 1**	**Variant 2**	**Variant 1**	**Variant 2**
$P^*_{i,t}$	−0.3111*** (0.1095)	−0.3341*** (0.1019)	−0.0124 (0.0078)	−0.0096 (0.0086)
$\Delta Costs_{i,t}$	−0.2147 (0.2165)	−0.2413 (0.2048)	−0.0866 (0.2044)	−0.0753 (0.2158)
$\Delta SR^{down}_{i,\,t\text{-}1} \times Stock_i$	0.4842*** (0.0885)	0.4524*** (0.0928)	0.1985* (0.1096)	0.1820 (0.1187)
$\Delta SR^{down}_{i,\,t\text{-}1} \times Mutual_i$	0.5914*** (0.0885)	0.5475*** (0.0676)	0.1960*** (0.0701)	0.1707** (0.0830)
$Critical_{i,t-1}$		0.3054*** (0.0423)		0.0768 (0.0781)
$\Delta P_{i,t-1}$			0.0236 (0.3157)	0.0561 (0.3283)
R^2 (within)	0.3978	0.4207		
Sargan–Hansen test (p-value)			0.7588	0.4592
Arellano–Bond test AR(1) (p-value)			<0.0001	0.0003
Arellano–Bond test AR(2) (p-value)			0.1080	0.1918
Num firms	58			
Num observations	348			

Note: The table shows estimated coefficients and robust standard errors (clustered at the firm level) in brackets. Year dummies are included, but not reported. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The variable $\Delta Costs_{i,t}$ defines the log change in costs, $\Delta P_{i,t-1}$ is the log premium growth, $SR^{\text{down}}_{i,t-1}$ is the log decrease in solvency ratio, and $P^*_{i,t}$ represents the log premiums. The dummy variables $Stock_i$ and $Mutual_i$ take one if firm i is a stock or mutual insurer, respectively. The dummy variable $Critical_{i,t-1}$ takes one if firm i reported a solvency ratio of below 110%.

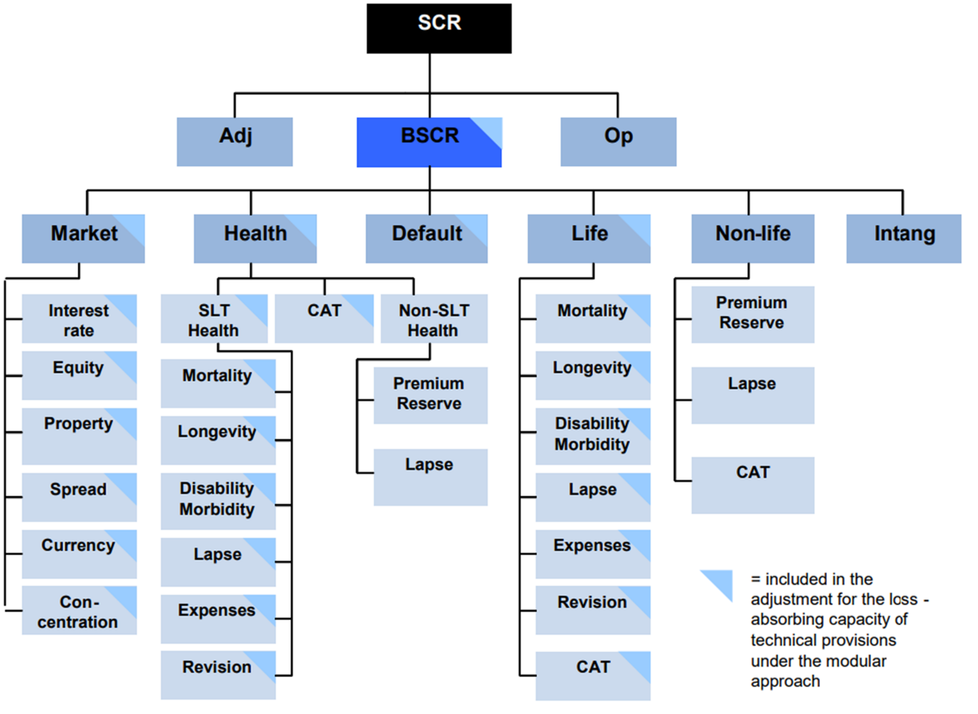

FIGURE A1 Risk (sub-)modules of the Solvency II standard formula (see European Insurance and Occupational Pensions Authority EIOPA, 2014). The SCR is calculated as the sum of basic solvency capital requirements (BSCR), capital requirements for operational risks (Op), and an adjustment for loss-absorbing capacity of technical provisions and deferred taxes (Adj) (see Directive 2009/138/EC Article 103).

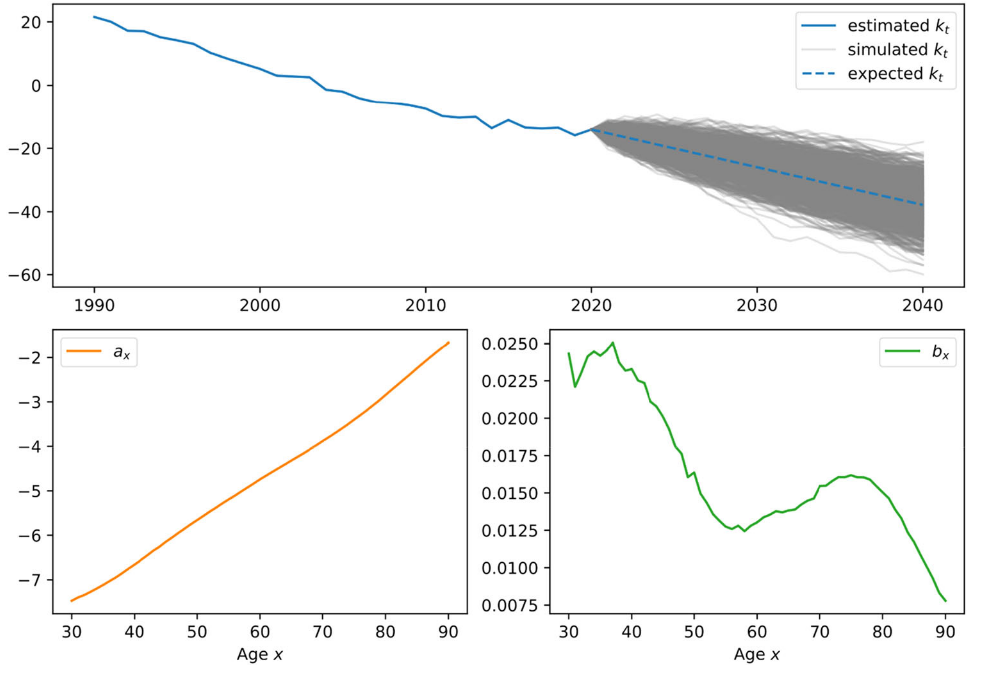

FIGURE A2 Calibration of the mortality model. The upper figure shows the estimated parameters k_t of the Lee–Carter model along with 1000 simulations and the expected values under the fitted random walk with drift. The lower two figures show the estimated parameters a_x and b_x of the Lee–Carter model.