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CASE STUDY



A COVID-19 stress test for life insurance: insights into the effectiveness of different risk mitigation strategies

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Abstract

COVID-19 has affected mortality rates and financial markets worldwide. Against this background, we perform a COVID-19 stress test for life insurance, considering a joint financial and mortality shock, to evaluate the effectiveness of different risk mitigation strategies. Specifically, we conduct a model-based simulation analysis of a life insurer selling annuities and term life insurances. The analysis includes stress scenarios that are calibrated to observations during the first year of the COVID-19 pandemic. We also consider new business and study the risk situation under three different risk mitigation strategies observed in practice as an immediate response to the pandemic: stopping sales, increasing premiums, or adjusting investment strategies. Results show that a life insurer's risk situation is mainly affected in the short term, selling annuities (in addition to term life insurance) immunizes against the mortality shock, and the immediate use of risk mitigation strategies can help reduce the negative impact.

Keywords Life insurance \cdot Stress test \cdot COVID-19 \cdot Risk mitigation strategies \cdot Asset–liability model

JEL Classification $G22 \cdot G23 \cdot G32 \cdot J11$

1 Introduction

COVID-19 had and will continue to have a major impact on society worldwide. Under the backdrop of globalization, the virus spread quickly across countries, thereby increasing mortality rates and causing many economic problems, such as business interruptions and supply chain issues. The COVID-19 pandemic is thus

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notable not only for its impact on human health and mortality [29, 36] but also for its economic effects on financial markets [1, 43]. This makes it particularly relevant for the life insurance industry, whose core business is to adequately price mortality risks and ensure stable returns on assets under management.

Research by a U.S. company that uses data science to predict disease outbreaks indicates an increasing frequency of pandemics, revealing a 47-57% chance of a COVID-19-like event happening within the next 25 years [30]. Hence, managing pandemic shocks is highly relevant for life insurers. Although the previous literature has examined the general impact of COVID-19 on the insurance industry [34], particularly with respect to mortality risk [10, 33, 37] or insurance investing [27], academic research that analyzes the impact of the joint financial and mortality shock caused by COVID-19 on a life insurer's risk situation in an asset-liability-based simulation analysis is still missing. Further, Harris et al. [22] showed that U.S. life insurers only sparingly responded to COVID-19 by removing specific policies or increasing premiums for newly sold policies for older people. However, the effectiveness of these immediate measures has not been analyzed in academic research so far. Against this background, we examine the impact of a joint financial and mortality shock on a life insurer's risk situation in a COVID-19 stress test. Furthermore, we evaluate the effectiveness of different risk mitigation strategies observed in practice that can be applied on short notice to draw conclusions for potential future pandemics. We find that a temporary pandemic event such as COVID-19 affects a life insurer's risk situation, especially in the short run, and that the immediate use of risk mitigation strategies can reduce the negative impact.

COVID-19 has increased mortality rates differently across population groups, with older individuals or those with comorbidities being the most affected [11, 29]. Spiegelhalter [38] and Sasson [36] proposed that COVID-19 caused an upward loglinear shift in mortality rates, affecting older individuals more. Schnürch et al. [37] described how to embed this shift in the popular Lee–Carter (LC) mortality model. Furthermore, they studied the impact of a COVID-19-like mortality shock on the valuation of life insurance products, similar to Carannante et al. [10] who conversely used an accelerated mortality model. Carannante et al. [9] examined the profitability of variable annuity contracts under a COVID-19-induced mortality shock, similar to Cheng [13] who focused on participating life insurance and considered changes in policyholders' surrender behavior. While these existing studies observed only a limited impact of mortality shocks on life insurance, they did not consider joint financial and mortality shocks. Even before COVID-19, empirical research indicated that mortality and financial risks could be correlated [16] and some studies have explicitly investigated the consequences for the risk-neutral valuation of life insurance products [2, 17, 23, 28]. In the context of COVID-19, Li et al. [26] used excess mortality and interest rate data from the COVID-19 pandemic in the U.S. to calibrate a bivariate jump diffusion model for the risk-neutral pricing of mortality bonds and observed a high correlation between mortality and interest rates during the pandemic. Furthermore, Arık et al. [3] found only a small relevance of simultaneous financial and mortality shocks for the risk-neutral pricing of annuities and buyout premiums. In contrast to previous studies, we focus on a life insurer's risk situation and the effectiveness of risk mitigation strategies rather than risk-neutral valuation.

Regarding the observed risk mitigation strategies of life insurers as an immediate response to COVID-19, Harris et al. [22] observed only a few adjustments to product pricing and offerings in the U.S.; these adjustments include slightly increased premiums by low-price leaders, increased prices for high-risk groups (e.g., smokers), and removal of specific policies offered to older people from the market. Similarly, U.S. life insurers during the Spanish flu of 1918 charged higher prices for new policies and gave up business in states with greater exposure to the disease [14]. Regarding investment strategies, Berry-Stölzle et al. [5] observed that U.S. life insurers created cash buffers by raising external capital and cutting dividends in response to the 2008–2009 financial crisis; the same approach was also observed during the COVID-19 pandemic [19]. Another common strategy is to shift assets into low-risk investments (e.g., government bonds) to avoid higher volatility caused by financial crises [24]. However, investments in bonds are exposed to credit risk, which is highly relevant for insurance investments, as downgrades by rating agencies increased during the COVID-19 pandemic [27]. In line with the academic literature, regulatory stress tests by the European and Occupational Pension Authority (EIOPA) and the Australian Prudential Authority (APRA) showed that reactive management actions, such as de-risking of assets or raising capital, can help reduce the negative impact of a COVID-19-like stress scenario [18]; the common management actions used by insurers are capital raising, reduction of new business volumes, and repricing [4].¹ Building on these observations, we consider three risk mitigation strategies in our stress test: premium increases for new business, age-specific adjustments of product offerings during the pandemic, and changes in the life insurer's investment strategy at the beginning of the pandemic.

For the model framework of our stress test, we build on previous research that used asset–liability models to study the effectiveness of natural hedging² [20, 42] or mortality bonds [12, 21] as risk mitigation strategies. In contrast to these studies, we consider a joint financial and mortality shock calibrated to COVID-19 and analyze the effectiveness of immediate measures rather than risk mitigation strategies that had to be initialized in the past. For the mortality model of our simulation analysis, we follow Gatzert and Wesker [20] and use an extension of the LC model proposed by Brouhns et al. [8]. To embed the mortality shock, we employ the approach of Schnürch et al. [37] using mortality data from the first year of the COVID-19 pandemic. For the asset model, we differentiate between high- and low-risk investments. Both evolve according to a geometric Brownian motion, and the life insurer specifies the portfolio composition (as in Bohnert et al. [7]) making adjustments in response to the pandemic outbreak possible. To include financial shocks depending on the risk levels of investment types, we use financial data from the first year

¹ Note that regulatory stress tests consider joint financial and mortality shocks but apply many simultaneous shocks to complex balance sheets relying on standard formulas, rarely consider multi-timestep internal models, and most often present results in an accumulated way.

 $^{^2}$ The literature on natural hedging shows that selling annuities next to term life insurance is an effective tool to hedge against mortality risks and to smooth cash flow structures in general [20, 42].

of the COVID-19 pandemic and consider market and credit risks. The life insurer's asset–liability model accounts for regular dividend payments to shareholders and new business (term life and annuity). Policies are actuarially calculated with additional loadings sold to different age groups, allowing the assessment of the effectiveness of premium increases or age-specific adjustments in product offerings during the pandemic.

We run Monte Carlo simulations to analyze the long- and short-term effects of individual and joint financial and mortality shocks on a life insurer's risk situation under different product portfolios (term life vs. annuity). Furthermore, we evaluate the effectiveness of the three risk mitigation strategies to reduce the negative impact of the joint financial and mortality shock for a life insurer particularly focusing on term life insurance. Our results show that financial and mortality shocks reinforce each other. The stress scenario increases the life insurer's one-year default probabilities during the pandemic but exerts only a small long-term impact on the life insurer's risk situation. A sufficiently large portion of annuities in the product portfolio immunizes against the mortality shock but only partially immunizes against the financial shock. Furthermore, the risk mitigation strategies reduce the negative short-term impacts, with the effectiveness depending on the respective strategies.

The remainder of this paper is organized as follows: Sect. 2 introduces the mortality and asset models with embedded shock mechanisms along with the life insurer's asset–liability model. Section 3 explains the calibration of the financial and mortality shock based on COVID-19 and the parameters used in the simulation analyses. The numerical results are presented by first examining the long- and short-term effects of the (joint) shocks and then analyzing the effectiveness of different risk mitigation strategies. Finally, Sect. 4 summarizes the main findings.

2 Model framework

In this section, we describe the model framework used in our simulation analysis to study the impact of a joint financial and mortality shock, as exemplified by COVID-19, on life insurance. We first describe the mortality model with a mortality shock, followed by the asset model with a financial shock, and finally, the life insurer's asset–liability model.

2.1 Mortality model with shock

The mortality model describes the development of mortality rates for a given population. The mortality rate m(x, t) of an x-year-old person in year t is defined as

$$m(x,t) = \frac{D(x,t)}{E(x,t)},$$
(1)

where D(x, t) is the death count and E(x, t) is the exposure at risk. Given the mortality rates in Eq. (1), the corresponding one-year survival probability of an *x*-year-old person in year *t* can be computed using $p_x(t) = \exp(-m(x, t))$, and the

one-year death probability is $q_x(t) = 1 - p_x(t)$ [8]. The probability ${}_np_x(t)$ that an *x*-year-old person in year *t* will survive for the next *n* years can be computed using ${}_np_x(t) = \prod_{i=0}^{n-1} p_{x+i}(t+i)$.

Building on Gatzert and Wesker [20], we assume that mortality rates follow the LC model [25], i.e.,

$$m(x,t) = \exp\left(a_x + b_x \cdot k_t + \varepsilon_{x,t}^m\right),\tag{2}$$

with age-specific constants a_x and b_x , time-varying trend k_t , and homoscedastic error terms $\varepsilon_{x,t}^m$ with a mean of zero. Although the model in Eq. (2) is underdetermined, adding the two constraints

$$\sum_{x} b_x = 1 \quad \text{and} \quad \sum_{t} k_t = 0 \tag{3}$$

ensures identifiability [25]. Furthermore, we use an extension of the LC model proposed by Brouhns et al. [8], where the death counts D(x, t) are given by a Poisson distribution, i.e.,

$$D(x,t) \sim Poisson(E(x,t) \cdot \hat{m}(x,t))$$
 with $\hat{m}(x,t) = \exp\left(a_x + b_x \cdot k_t\right)$

The unknown parameters a_x , b_x , and k_t are estimated by maximizing the corresponding log-likelihood function

$$L(a_x, b_x, k_t) = \sum_{x,t} \left(D(x, t) \cdot \left(a_x + b_x \cdot k_t \right) - E(x, t) \cdot \exp\left(a_x + b_x \cdot k_t \right) \right)$$

using Newton's method, where the constraints in Eq. (3) are applied after each update step [8]. To forecast mortality rates beyond the time of observation, the estimated parameters k_i are used to fit a time series model. Lee and Carter [25] employed a simple random walk with drift, i.e.,

$$k_{t+1} = \phi + k_t + \varepsilon_t, \tag{4}$$

where ϕ is a constant drift and ε_t denotes independent normally distributed random variables with a mean of zero and constant volatility σ .³

In year $t = \tilde{t}$, a pandemic event occurs and increases mortality in this specific year. To model the mortality shock in year \tilde{t} , we build on the empirical observations during COVID-19, showing that the increase is age-specific and can be approximated by an upward log-linear shift for the 25–84 age group [36, 37]. Therefore, following Schnürch et al. [37] we consider the adjusted mortality rate

$$m_{shock}(x,t) = \begin{cases} (1+c) \cdot m(x,t) & \text{if } t = \tilde{t} \\ m(x,t) & \text{else} \end{cases}$$
(5)

 $^{^{3}}$ Note that more sophisticated time series models (e.g., ARIMA models) can be considered too [20, 25] and that the random walk with drift could be replaced by a Brownian motion with drift in a continuous time model [6].

for a strictly positive constant *c*. Assuming that m(x, t) and $m_{shock}(x, t)$ follow an LC model, Schnürch et al. [37] mathematically proved that the only difference between the two LC models is approximately given by an increase in $k_{\tilde{t}}$ without affecting k_t in other years $t \neq \tilde{t}$ or the parameters a_x and b_x . Therefore, we employ a single LC model in our stress test, where parameter k_t is increased by a strictly positive constant k_{shock} in the year of the pandemic event \tilde{t} , i.e.,

$$k_t^{shock} = \begin{cases} k_t + k_{shock} & \text{if } t = \tilde{t} \\ k_t & \text{else} \end{cases}, \quad a_x^{shock} = a_x \text{ and } b_x^{shock} = b_x$$

2.2 Asset model with financial shock

The asset model accounts for two types of investments. A high-risk investment *S* represents stocks while a low-risk investment *B* represents bonds. As in Bohnert et al. [7], the asset prices I_t^i of both investments $i \in \{S, B\}$ evolve over time *t* according to the geometric Brownian motion, i.e.,

$$dI_t^i = \mu_i \cdot I_t^i \cdot dt + \sigma_i \cdot I_t^i \cdot dW_t^i$$

with drifts μ_i , volatilities σ_i , and Brownian motions W_i^i . The solutions for the stochastic differential equations are given by

$$I_t^i = I_{t-1}^i \cdot \exp\left(\mu_i - \frac{\sigma_i^2}{2} + \sigma_i \cdot \varepsilon_t^i\right)$$
(6)

with independent standard normally distributed random variables ε_t^i . Therefore, investments $i \in \{S, B\}$ yield a continuous one-year return of

$$r_t^i = \mu_i - \sigma_i^2 / 2 + \sigma_i \cdot \varepsilon_t^i.$$
⁽⁷⁾

To account for credit risk, the investments in bonds are reduced by the portfolio loss

$$L_t = EAD_t \cdot LGD_t \cdot \tilde{L}_t \tag{8}$$

with exposure at default EAD_t , loss given default LGD_t , and normalized portfolio loss \tilde{L}_t .⁴ The normalized portfolio loss is Vasicek distributed, i.e.,

$$\tilde{L}_t = \Phi\left(\frac{\sqrt{1-\rho} \cdot \varepsilon_t^L - \Phi^{-1}(PD_t)}{\sqrt{\rho}}\right),$$

⁴ The normalized portfolio loss \tilde{L}_t represents the loss of a large homogeneous portfolio consisting of N non-recoverable loans with equal values 1/N and equal default probabilities PD_t . Assuming that the assets of the borrowing companies are modeled by geometric Brownian motions with equal correlation parameters ρ , the normalized portfolio loss \tilde{L}_t converges for $N \to \infty$ against the Vasicek distribution [40].

where Φ denotes the standard normal distribution, PD_t denotes the default parameters, ρ denotes the correlation parameter, and ε_t^L denote independent standard normally distributed random variables.⁵ The correlations between ε_t^S , ε_t^B , and ε_t^L are denoted as ρ_{SB} , ρ_{SL} , and ρ_{BL} , respectively.

To model a financial shock in year \tilde{t} , we consider a price drop in combination with increased volatility for both investments $i \in \{S, B\}$, i.e.,

$$\varepsilon_t^i = \begin{cases} -|\varepsilon_t^i| & \text{if } t = \tilde{t} \\ \varepsilon_t^i & \text{else} \end{cases} \quad \text{and} \quad \sigma_i = \begin{cases} \sigma_i + \sigma_i^{shock} & \text{if } t = \tilde{t} \\ \sigma_i & \text{else} \end{cases}$$
(9)

for strictly positive constants σ_i^{shock} . Consequently, the asset prices in Eq. (6) become

$$I_t^i = \begin{cases} I_{t-1}^i \cdot \exp\left(\mu_i - \frac{(\sigma_i + \sigma_i^{shock})^2}{2} - (\sigma_i + \sigma_i^{shock}) \cdot |\varepsilon_t^i|\right) & \text{if } t = \hat{u} \\ I_{t-1}^i \cdot \exp\left(\mu_i - \frac{\sigma_i^2}{2}\right) + \sigma_i \cdot \varepsilon_t^i & \text{else} \end{cases}$$

and the returns in Eq. (7) become

$$r_t^i = \begin{cases} \left. \begin{array}{c} \mu_i - \left(\sigma_i + \sigma_i^{shock}\right)^2 \right/ 2 - \left(\sigma_i + \sigma_i^{shock}\right) \cdot \left|\varepsilon_t^i\right| & \text{if } t = \hat{t} \\ \mu_i - \sigma_i^2 / 2 + \sigma_i \cdot \varepsilon_t^i & \text{else.} \end{cases} \end{cases}$$

To account for an increased credit risk in year \tilde{t} , we use two different default parameters, i.e.,

$$PD_t = \begin{cases} PD^{shock} & \text{if } t = \tilde{t} \\ PD & \text{else.} \end{cases}$$
(10)

2.3 Asset-liability model

The asset-liability model of our stress test describes the situation of a life insurer who frequently writes new business over a time horizon of *T* years. Cash flows only arise at the beginning of year *t* denoted by t^+ or at the end of the year denoted by t^- . The life insurer is founded in year 1⁺ and sells term life insurance contracts with death benefit *D* as well as temporary annuities with annual payments *R*. Both types of contracts have a term of *T* years. The age *x* of the purchasing policyholders varies, and the number of contracts sold in year *t* to policyholders with age *x* is denoted by $n_D(x, t)$ for term life insurances and $n_R(x, t)$ for annuities.

Term life insurance contracts are sold against annual premiums while annuities are sold against single premiums. The premiums are actuarially fair with an additional loading λ and depend on the year of sale and the age of the purchaser, i.e.,

⁵ Note that this approach is motivated in the Capital Requirement Regulation of Basel III (see Regulation (EU) No 575/2013, article 153).

$$P_D(x,t) = (1+\lambda) \cdot D \cdot \frac{T | A_x^{(t)}}{\ddot{a}_{x:\overline{T}|}^{(t)}} \quad \text{and} \quad P_R(x,t) = (1+\lambda) \cdot R \cdot a_{x:\overline{T}|}^{(t)}.$$
(11)

The corresponding actuarial present values are given by

$${}_{T|}A_{x}^{(t)} = \sum_{k=0}^{T-1} v^{k+1} \cdot {}_{k}p_{x}(t) \cdot q_{x+k}(t+k), \quad \ddot{a}_{x:\overline{T}|}^{(t)} = \sum_{k=0}^{T-1} v^{k} \cdot {}_{k}p_{x}(t)$$

$$\text{and} \quad a_{x:\overline{T}|}^{(t)} = \sum_{k=1}^{T} v^{k} \cdot {}_{k}p_{x}(t),$$
(12)

where $v = 1/(1 + r^G)$ denotes the discount factor for some actuarial interest rate r^G .

When the life insurer is founded in year 1^+ , shareholders make an initial contribution E_0 , and the first contracts are sold, resulting in the insurer's initial asset volume of

$$A_{1^{+}} = E_0 + \sum_{x} n_D(x, 1) \cdot P_D(x, 1) + \sum_{x} n_R(x, 1) \cdot P_R(x, 1).$$

For the transition from t^+ to t^- , the fraction α of assets A_{t^+} is invested in stocks, and the fraction $(1 - \alpha)$ is invested in bonds. Accounting for the continuous interest rates for the stock investments r_t^S and bond investments r_t^B (see Eq. (7)), as well as the portfolio loss L_t (see Eq. (8)), the adjusted assets are given by

$$A_{t^{-}}^{adj} = \alpha \cdot A_{t^{+}} \cdot \exp\left(r_{t}^{S}\right) + \left((1-\alpha) \cdot A_{t^{+}} - L_{t}\right) \cdot \exp\left(r_{t}^{B}\right).$$
(13)

To define contractual payments at the end of the year, let $d_D(x, \tau, t)$ and $d_R(x, \tau, t)$ respectively denote the number of deaths in year *t* of the policyholders who bought a term life insurance contract or an annuity at the beginning of year τ at age *x*. Furthermore, let

$$\vec{n}_i(x, \tau, t) = n_i(x, \tau) - \sum_{k=\tau}^t d_i(x, \tau, k)$$
 : $i \in \{D, R\}$

denote the number of contracts bought in year τ by policyholders with age x who are still active in $t^{-.6}$ Given this notation, the adjusted assets in Eq. (13) are reduced by contractual payments, and some dividend div^7 is paid to shareholders, i.e.,

$$A_{t^{-}} = A_{t^{-}}^{adj} - D \cdot \sum_{\tau=1}^{t} \sum_{x} d_{D}(x,\tau,t) - R \cdot \sum_{\tau=1}^{t} \sum_{x} \vec{n}_{R}(x,\tau,t) - div.$$

The assets at the beginning of all years t > 1 are given by

⁶ For $\tau < 1$ and $t < \tau$, we set $\vec{n}_i(x, \tau, t) = 0$.

⁷ The dividend is calculated by $r_M \cdot E_0 = (1 - 0.005) \cdot div + 0.005 \cdot (-E_0)$ based on the assumption that the shareholders assume a constant one-year default probability of 0.5%, with r_M denoting the market rate of return [20].

$$A_{t^{+}} = A_{(t-1)^{-}} + \sum_{\tau=t-T}^{t-1} \sum_{x} P_{D}(x,\tau) \cdot \vec{n}_{D}(x,\tau,t-1) + \sum_{x} P_{D}(x,t) \cdot n_{D}(x,t) + \sum_{x} P_{R}(x,t) \cdot n_{R}(x,t).$$

Using the actuarial notation from Eq. (12), the value of liabilities in year t for a single term life insurance policy bought in year τ by an x-year-old person is

$$V_D(x,\tau,t) = D \cdot {}_{T-\vec{\tau}|} A_{x+\vec{\tau}}^{(t)} - P_D(x,\tau) \cdot \ddot{a}_{x+\vec{\tau}}^{(t)} \cdot {}_{\overline{x+\vec{\tau}}} \cdot \overline{T-\vec{\tau}} \cdot \overline{T-\vec{\tau}}$$

where $\vec{\tau} = t - \tau$ denotes the time since the contract was concluded. Similarly, the value of liabilities in year *t* for a single annuity contract bought in year τ by an *x*-year-old person is given by

$$V_R(x,\tau,t) = R \cdot a_{x+\vec{\tau}: \ \overline{T-\vec{\tau}}}^{(t)}.$$

Accounting for all active contracts at the end of year *t*, the life insurer's required policy reserves can be computed as

$$PR_{t^{-}} = \sum_{\tau=1}^{t} \sum_{x} \vec{n}_{D}(x,\tau,t) \cdot V_{D}(x,\tau,t+1) + \sum_{\tau=1}^{t} \sum_{x} \vec{n}_{R}(x,\tau,t) \cdot V_{R}(x,\tau,t+1).$$

To investigate the life insurer's risk situation, the one-year default probabilities DP_t and the overall default probability DP over the entire time horizon are considered. Accordingly, let $T_s = \inf \{t = 1, ..., T : A_{t^-} < PR_{t^-}\}$ denote the stopping time when the life insurer's assets drop below the policy reserves for the first time. Then, the overall default probability is given by

$$DP = P(T_s \le T),$$

and the one-year default probabilities are

$$DP_{t} = P(A_{t^{-}} < PR_{t^{-}} | A_{\tau^{-}} \ge PR_{\tau^{-}} \forall \tau < t) = \frac{P(T_{s} = t)}{P(T_{s} > t - 1)}$$

3 Numerical analysis

This section describes the calibration of the mortality and financial shocks based on observations from the first year of the COVID-19 pandemic, along with the parameters used in our simulation analysis. Subsequently, the numerical results of the simulation analysis are presented by first showing the impact of the joint financial and mortality shock on the life insurer's risk situation and then examining the effective-ness of the different risk mitigation strategies.



Fig. 1 Estimated parameters k_t for the LC model of Germany (a) and Spain (b) with specific forecast and pandemic shock

3.1 Calibration of mortality and financial shocks

COVID-19 affected mortality rates differently in geographic regions such as the EU because of differences in various aspects, such as political decision making or healthcare systems [41]. Therefore, we use Germany and Spain, two of the five largest EU countries by population, to calibrate two different and representative mortality shocks in our stress test. Germany has a particularly low crude mortality rate while Spain has a particularly high crude mortality rate caused by COVID-19 [41]. For both countries, the parameters of the LC model given in Eq. (2) are estimated using mortality data from 1990 to 2019 provided by the Human Mortality Database. Age *x* is restricted to 25–85 years to ensure the adequacy of an upward log-parallel shift in mortality, as observed during the COVID-19 pandemic [36, 37].

To forecast mortality rates beyond the year 2019 with the two LC models, we use the estimated parameters k_t to fit a random walk with drift (see Eq. (4)). Similar values are obtained for both countries: $\phi^{Ger} = -1.37$ for Germany and $\phi^{Spa} = -1.72$ for Spain, with standard deviations $\sigma^{Ger} = 1.57$ and $\sigma^{Spa} = 2.90$, respectively, for the error terms ε_t . Figure 1 shows the estimated parameters k_t for both countries along with a specific forecast until the year 2060, with the general trend shifting to higher longevity. The estimated parameters a_x and b_x are shown in the Appendix (see Fig. 9). For both countries, a_x steadily increases for age x while b_x indicates a higher sensitivity toward the time trend parameter k_t for ages around 30 and 75 years. Only for x < 35 years is parameter a_x lower for Germany than for Spain; for these ages, parameter b_x is clearly higher for Spain than for Germany. As a result, we observe



Fig.2 Impact of COVID-19 on European stock and bond markets. Notes: The subfigures **b** and **c** show the rolling volatility σ estimated at an annual level with monthly data of the European stock or bond market index

higher mortality rates for Germany than for Spain in our model owing to the longevity trend (see also Eq. (2)).⁸

To include the pandemic shock in year 2020, we replace the parameters k_{2020} with estimates of two additional LC models fitted on mortality data including the year 2020 [37]. For both countries, a jump in the pandemic year 2020 runs counter to the general demographic trend (see Fig. 1). In line with the observations by Villani et al. [41], the jump from -18.23 to -15.24 ($k_{shock} = 2.99$) for Germany is less pronounced (see Fig. 1a) while the jump from -27.11 to -13.63 ($k_{shock} = 13.48$) for Spain is more pronounced (see Fig. 1b).

As exemplified by COVID-19, a pandemic event can also influence financial markets [1, 43]. To calibrate a realistic stress scenario in the stress test, we exemplarily

⁸ Note that this observation is in line with the higher life expectancy in Spain than Germany [32].



Fig. 3 Moody's rated sovereign bond defaults since 1983 [31]

analyze the impact of COVID-19 on the European stock performance index "S&P Europe 350" and "S&P Eurozone Sovereign Bond Index".⁹ While Fig. 2a shows that COVID-19 had a strong impact on the stock market index, with a sharp decline in 2020, only a small impact can be observed on the bond market index; this result is in line with the general observations during financial crises [24]. Furthermore, Fig. 2b, c show that COVID-19 increased the stock and bond markets' volatility at an annual level, with the effect being particularly more pronounced for the stock market. Building on these empirical observations, we set $\sigma_S^{shock} = 0.10$ and $\sigma_B^{shock} = 0.01$ in Eq. (9) to represent the observed increase in volatility in 2020 (see Fig. 2b, c).

Although investments in bonds are often assumed to be safe havens during financial crises [24], as supported by the results in Fig. 2, they are exposed to credit risk. The large number of downgrades made by financial rating agencies during the COVID-19 pandemic suggests that credit risk increased during this period [27]. As shown in Fig. 3, the highest number of sovereign bond defaults rated by Moody's occurred in the first year of COVID-19 in 2020. The annual default rate in 2020 was 4.2% while the average annual default rate between 1983 and 2021 was 0.8%. Building on this observation, we assume increased portfolio loss $L_{\tilde{t}}$ in the pandemic year by setting $PD^{shock} = 4.2\%$ and PD = 0.8% in Eq. (10).

3.2 Input parameters

For the asset–liability model of the life insurer, we use a time horizon of T = 20 years and a death benefit of D = €100,000, representing the default values for term life insurance on Germany's largest aggregator, www.check24.de. In this study, we assume that starting with year 1 every year, 9000 new term life insurance contracts

⁹ In contrast to our approach for the mortality shock, we do not differentiate between Germany and Spain for the financial shock as the sales area is most often geographically restricted to the country of origin; the same does not hold true for financial markets.

are sold, split into three batches of size 3000 for the different age groups of x = 30, x = 40, and x = 50 years,¹⁰ i.e.,

$$n_D(x,t) = \begin{cases} 3000 & \text{if } x \in \{30, 40, 50\} \\ 0 & \text{else.} \end{cases}$$

We also accept that every year n_R temporary annuities with an annual annuity payment of R = 66000 are sold to a single age group of x = 65 years. The number of annually sold annuities n_R is subject to a sensitivity analysis in Sect. 3.3 and then hold constant at $n_R = 50$ for the remaining analyses. For the actuarial present values in Eq. (12), the mortality forecasts of the two fitted LC models (Germany and Spain) are utilized. The actuarial interest rate r^G is set to 0.25%, representing the legal requirement for German life insurers in 2023. We present the results under actuarially fair premiums using the premium loading $\lambda = 0$. The shareholders' initial contribution E_0 is accepted to be 3% of the initially sold contracts' present value.

To estimate the drift, volatility, and correlation of the stock and bond investment, we employ the monthly data of the stock market index "S&P Europe 350" and "S&P Eurozone Sovereign Bond Index" from February 2013 to December 2021 and obtain $\mu_S = 0.095$, $\sigma_S = 0.142$, $\mu_B = 0.033$, $\sigma_B = 0.037$, and $\rho_{SB} = 0.143$. The stock ratio α is set to 15%.¹¹ For the market rate of return r_M , which is used only to calculate dividends in this simulation analysis, we use the same value of 5% as in Gatzert and Wesker [20]. For the portfolio loss L_t in Eq. (8), the exposure at default is set as the fraction of assets invested in bonds, i.e., $EAD_t = (1 - \alpha) \cdot A_{t^+}$. The loss given default is set to $LGD_t = 47\%$ while the correlation parameter is set to $\rho = 0.20$.¹² Furthermore, we assume no correlation between portfolio loss and investment returns in this simulation, i.e., $\rho_{SL} = \rho_{BL} = 0$.

In the following analyses, all numerical results are obtained using Monte Carlo simulations with 500,000 sample paths. Depending on the section, calibrated financial and/or mortality shocks are applied (see Sect. 3.1), where the year of the pandemic event is set to the 10th year after the life insurer's founding, i.e., $\tilde{t} = 10$. Table 1 summarizes the parameters used in the simulation analysis.

¹⁰ While the number of contracts is chosen to be equal for the different age groups to increase the interpretability of the results, the selection of the 30-, 40-, or 50-year-old purchasers is motivated by the research showing that the probability of owning term life insurance is highest for the age group of 50–59 years [39].

¹¹ According to the German Insurance Association, 83.4% of the assets of German life insurers consisted of bonds and real estate while shares and participating interest accounted for 14.0% in 2022 (see www.gdv.de).

¹² The loss given default of 47% derives from an average recovery rate on defaulted sovereign bonds over the 1983–2021 period of 53% [31]. Furthermore, inserting the average annual default rate of 0.8% over the same period in the standard formula of the Capital Requirement Regulation of Basel III yields the correlation parameter of 20% (see Regulation (EU) No 575/2013, article 153).

Description	Notation	Value
Time horizon	Т	20
Time of the pandemic event	\tilde{t}	10
Number of annually sold term life policies	n _D	9000
Policyholders' age groups (term life insurance)	x_D	30, 40, 50
Death benefit	D	100,000
Number of annually sold annuities	n_R	50
Policyholders' age groups (annuity)	x_R	65
Annual annuity	R	6000
Premium loading	λ	0.000
Drift of high-risk investment (stocks)	μ_S	0.095
Volatility of high-risk investment (stocks)	σ_S	0.142
Drift of low-risk investment (bonds)	μ_B	0.033
Volatility of low-risk investment (bonds)	σ_B	0.037
Correlation between high- and low-risk investment	$ ho_{SB}$	0.143
Correlation between portfolio loss and investment return	$\rho_{SL}; \rho_{BL}$	0.000
Stock ratio	α	0.150
Loss given default	LGD	0.470
Default probability parameter of the Vasicek distribution	PD	0.008
Correlation parameter of the Vasicek distribution	ρ	0.200
Market rate on return	r_M	0.050

 Table 1
 Parameters for analysis

3.3 Impact of COVID-19 shock on life insurer's risk situation

The COVID-19 stress test consists of two parts: the financial shock, which is equal for Germany and Spain; and the mortality shock, which is more pronounced for Spain than for Germany (see Sect. 3.1). Figure 4a shows the overall default probability DP over the entire time horizon of T = 20 years when no shock is applied depending on the number of annually sold annuities n_R for Germany and Spain. As separate mortality models are calibrated for both countries, the results differ between Germany and Spain even in the absence of the mortality shock. If the life insurer sells only term life insurance $(n_R = 0)$, the overall default probabilities DP for Germany and Spain are 12.18 and 14.83%, respectively. Germany's lower default probability can be explained by its higher mortality rates (see Sect. 3.1), which result in shorter durations until death and thus less volatile cash flows (see also [42]). For both countries, the lowest default probability DP can be observed when a small amount of $n_R = 100$ annuities is sold every year, in addition to the term life insurance; it then steadily increases for higher numbers of annually sold annuities n_R . This finding is in line with Gatzert and Wesker [20] and can be explained by the smoother and, therefore, less volatile cash flow structures of mixed portfolios consisting of annuities and term life insurances.

Figure 4b shows the absolute increase in *DP* caused by the mortality and/or financial shocks in t = 10. In comparison with that in Germany, the more pronounced



(b) Scenario with financial and/or mortality shock

Fig. 4 Default probability *DP* when no financial or mortality shock is applied (**a**) and the absolute increase in *DP* caused by the financial and/or mortality shock in year t = 10 (**b**) depending on the number of sold annuities n_R for Germany and Spain

mortality shock in Spain leads to a higher increase in DP. Meanwhile, the financial shock increases DP approximately equally for Germany and Spain. For both countries, the increase in DP caused by the pure financial shock is greater than that caused by the pure mortality shock. Higher numbers of annually sold annuities reduce the negative impact of the financial shock until a saturation point of approximately 3.5 percentage points. However, the mortality shock can be completely absorbed by natural hedging [20, 42]. If both shocks are applied simultaneously, the increase in DP exceeds the sum of the individual shocks through an additional reinforcement effect (see Fig. 4b). The extent of the reinforcement effect decreases as the number of annually sold annuities increases, further emphasizing the benefits of natural hedging.

These results show that a diversified life insurer is relatively well immunized against the pure mortality shock caused by COVID-19 but that natural hedging cannot mitigate the risks caused by the simultaneous financial shock. As a life insurer's

	Germany		Spain	
	DP	Absolute increase	DP	Absolute increase
No shock	9.29%		10.12%	
Financial shock	15.13%	+ 5.84 p.p	15.59%	+5.47 p.p
Mortality shock	9.47%	+0.18 p.p	10.88%	+0.76 p.p
Both shocks	16.11%	+6.82 p.p	19.42%	+9.30 p.p

Table 2 Default probabilities *DP* in case of $n_R = 50$ for Germany and Spain caused by the financial and/ or mortality shock in t = 10

Notes: The absolute increase is expressed in percentage points (p.p.)



Fig. 5 Absolute increase of one-year default probabilities DP_t when the joint financial and mortality shock is applied in t = 10 or in t = 10 and t = 11 for Germany (**a**) and Spain (**b**)

product mix cannot be adjusted at short notice and doing so might not even be possible because of a specific market orientation, the following analyses focus on a life insurer with a high share of term life insurance, i.e., we set $n_R = 50.^{13}$ The default probabilities for this scenario are listed in Table 2.

To investigate the short- and long-term effects of a COVID-19-like event, we present in Fig. 5 the absolute increase of the one-year default probabilities DP, caused by the joint financial and mortality shock in t = 10 (filled bars). The years before the pandemic outbreak (t < 10) are not displayed as the one-year default probabilities are not affected until that point of time. For Germany (Fig. 5a) and Spain (Fig. 5b), the highest increase in the one-year default probabilities can be seen right at the end of that year. For later years, the increase exponentially decreases and converges against zero. The long-term effects result from the life insurer's reduced equity leading to higher default probabilities in the subsequent years as reserves must first be rebuilt. Although the increase for Spain starts at a higher level (7.90 percentage points) than that for Germany (5.44 percentage points), the convergence toward zero is similarly fast for both countries, falling below 0.2 percentage points four years after the end of the pandemic. As mortality rates are only increased in t = 10, higher payments for term life insurance are limited to this period too, as is the reduction of the life insurer's assets caused by the temporary financial shock. Therefore, the longterm impact is comparatively small. This result is in line with the findings of Carannante et al. [10], who showed that a temporary mortality shock would have a minor impact on life insurance, whereby the required premium increase to compensate an accelerated mortality decreases for longer contract terms.

Motivated by previous events such as the 1918 Spanish flu or the 2004 earthquake, mortality shocks are usually assumed to be short-term catastrophes that do not extend over several years [12, 15]. However, the case of COVID-19 indicates that a large-scale pandemic can increase mortality rates in the span of more than one year. Therefore, Fig. 5 also shows the impact of a two-year pandemic event in our stress test (unfilled bars), where the financial and mortality shocks are applied in years t = 10 and t = 11. In this case the one-year default probabilities first increase until the end of t = 11 and then again converge against zero. The higher increase in t = 11 may be explained by the life insurer's already reduced reserves caused by the shocks in t = 10, resulting in a worse financial starting point for the life insurer to enter the second year of the pandemic. As the decrease after the end of the two-year shock is exponential, as in the case of the one-year shock, the long-term impact for life insurance seems negligible even if the pandemic extends over several years.

3.4 Risk mitigation in the event of shocks

In this section, we investigate the effectiveness of different risk mitigation strategies to reduce the impact of the joint financial and mortality shock. We restrict our analysis to observed practices that can be applied on short notice, namely, stopping new business, increasing premiums, and adjusting investment strategies. Furthermore, we build on the results described in the previous section, showing that the impact of the shocks is short term regardless of the duration of the pandemic. Thus, we

¹³ Note that in this case, the premium volume of annuities is approximately 8.7% (11.2%) of the total premium volume in the case of Germany (Spain).



Fig. 6 Absolute increase in the one-year default probabilities DP_t caused by the joint financial and mortality shock in t = 10 for Germany (**a**) and Spain (**b**) if term life insurance policies are sold only to specific age groups in $t = 10^+$

focus on the joint shock only applied in year t = 10, with the different risk mitigation strategies applied directly at the beginning of that year in $t = 10^+$. Although this approach would mean that the life insurer anticipates the pandemic before it starts and responds immediately, this point in time serves as a threshold, i.e., a lower bound, owing to the used time steps of one year.¹⁴

3.4.1 Stopping new business

For the first risk mitigation strategy, we analyze the effectiveness of stopping new business for specific age groups during the pandemic. This strategy is motivated by the empirical findings of Harris et al. [22], who showed that some U.S. life insurers stopped selling specific policies for the oldest age groups in response to COVID-19.

Figure 6 shows the absolute increase in the one-year default probabilities DP_t caused by the joint financial and mortality shock in t = 10, when in $t = 10^+$, the term life insurance contracts are sold to all age groups, or only to the age groups x = 30 and x = 40 years, or only to the age group x = 30 years, or no term life insurance contracts are sold. The number of sold contracts is 3000 for all age groups and remains unchanged for all years before and after t = 10. The more age groups are excluded, the higher the risk reduction as the height of the four consecutive bars

¹⁴ Note that similar results regarding the effectiveness of the different risk mitigation strategies are obtained when the shocks extend over two consecutive years and the strategies are applied at the beginning of the second year.

decreases. The largest risk reduction can be observed at the end of the pandemic year t = 10, and it then exponentially decreases over time, analogous to the general decline in risk reduction potential. Therefore, the analyzed strategy indeed mitigates the increase in the one-year default probabilities caused by the pandemic shock. Stopping new business during the pandemic reduces the number of sold contracts and, therefore, reduces exposure toward the mortality shock. However, as most contracts are sold before the pandemic and the strategy does not address the financial shock, the effectiveness of this strategy is relatively small and offsets only approximately 14% of the increased one-year default probability in t = 10.

Furthermore, solely excluding the oldest age group, in anticipation of the greater increase in mortality for this group, is not optimal. Stopping new business for all the three age groups (unfilled bars with dashed lines) is more than three times as effective as solely excluding the oldest age group x = 50 (unfilled bars with solid lines). Table 3 in the Appendix shows the overall default probability under all possible combinations of age-specific exclusions for the new term life business in year t = 10. Some benefits are observed with the exclusion of older over younger individuals. However, a robustness test revealed that these benefits stem from the higher premium volumes for the contracts sold to older age groups due to their higher death probabilities rather than the greater increase in their mortality rates given the mortality shock in Eq. (5). When using age-specific death benefits in our simulation analysis to ensure that the premium volumes depend only on the number of sold contracts, we observe a higher risk reduction for excluding the younger age groups than for excluding the older age groups. Specifically, the risk for term life insurance decreases with age as the liability value becomes less volatile owing to the shorter duration until death at older ages [42]. Consequently, the general riskiness of a life insurance product can play a more important role and should not be neglected even if the mortality shock is more pronounced for older people (as in the case of COVID-19).

3.4.2 Increasing premiums

For the second risk mitigation strategy, we analyze the effectiveness of increasing actuarial fair premiums for contracts sold during the pandemic event by an additional loading. Therefore, different loadings λ for the contracts sold in $t = 10^+$ are used in Eq. (11) in the simulation analysis. The premiums before and after t = 10 are unchanged, i.e., actuarial fair premiums with $\lambda = 0\%$.

Figure 7 shows the absolute increase in the one-year default probabilities DP_t caused by the joint financial and mortality shock in t = 10 for different loadings λ . The loading $\lambda = 0\%$ (filled bars) serves as a reference point, where actuarial fair premiums are used during the pandemic. For the loadings $\lambda > 0\%$, the increase in the one-year default probabilities is reduced with the largest risk reduction at the end of the pandemic year in t = 10. As higher loadings increase the life insurer's equity and thus help to avoid liquidity shortage, this strategy addresses the negative impact of the financial and mortality shocks; by contrast, stopping new business during the pandemic only addresses the negative impact of the mortality shock on newly sold contracts. Hence, using a comparatively small loading of $\lambda = 2\%$ for the contracts



Fig. 7 Absolute increase in the one-year default probabilities DP_t caused by the joint financial and mortality shock in t = 10 for Germany (**a**) and Spain (**b**) if additional loadings λ for the contracts sold in $t = 10^+$ are used

sold in year $t = 10^+$ reduces the one-year default probabilities more than stopping the sale of all term life insurance contracts during the pandemic (see Figs. 6 and 7). Moreover, a sufficiently large loading can fully offset the increase in the one-year default probabilities DP_t . For Germany, the loading of $\lambda = 23\%$ completely negates the increase in DP_t caused by the joint financial and mortality shock in t = 10 for all $t \ge 10$ (see Fig. 7a).¹⁵

This mechanism makes premium increases a hypothetically attractive short-term strategy. However, in practice, this strategy carries the risk of losing a leading market position to competitors, which can result in a decline in demand in subsequent years. This assumption is also supported by Harris et al. [22], who observed that the premium response of U.S. life insurers to COVID-19 was minimal and limited to life insurers with a certain price gap toward competitors. Meanwhile, policyholders might even accept premium increases during a pandemic event because of the stronger sensitization toward death and, therefore, a higher willingness to pay for term life insurance [35]. Assuming that the premium increase, this condition would technically result in a combined strategy of stopping new business and increasing premiums, which would (in our simulation) be superior to the sole strategy of stopping new business.

¹⁵ For further information, Table 4 in the Appendix contains values for the overall default probability *DP* under the different loadings used in $t^+ = 10$.



Fig. 8 Absolute increase in the one-year default probabilities DP_t caused by the joint financial and mortality shock in t = 10 for Germany (a) and Spain (b) if the stock ratio α is adjusted in $t = 10^+$

3.4.3 Adjusting investment strategies

For the third risk mitigation strategy, we analyze the effectiveness of changing the investment strategy at the beginning of the pandemic year. We assume that the stock ratio α in Eq. (13) is reduced at $t = 10^+$ and remains constant for the remaining time horizon to account for the long-term nature of bonds. Higher shares in bonds generally reduce asset volatility and the exposure toward the volatility shock; this effect is less pronounced for bonds than for stocks in our stress test (see Fig. 2b, c). However, in our stress test, bond investments are exposed to credit risk, which is increased by the financial shock (see Sect. 3.1). Figure 8 shows the absolute increase in the one-year default probabilities DP_t caused by the joint financial and mortality shock in year t = 10 for different adjustments of the stock ratio α in $t = 10^+$. The stock ratio $\alpha = 15\%$ (filled bars) serves as a reference point, where the investment strategy remains unchanged.

Reducing the stock ratio α at the beginning of the pandemic decreases the absolute increase in DP_t in t = 10 to a minimum of 3.67 (5.63) percentage points for Germany (Spain) if all assets are reallocated to bonds, i.e., $\alpha = 0\%$ (see Fig. 8). Thereby, the largest step-wise reduction effect of 0.80 (0.96) percentage points for Germany (Spain) is obtained with the reduction of α from 15 to 10% while the smallest step-wise risk reduction of 0.39 (0.55) percentage points is obtained with the reduction of α from 5 to 0%. In later years, the one-year default probabilities DP_t start to increase again at some point $t \ge 11$, which happens earlier and is more pronounced for lower stock ratios α . This observation is consistent for both countries, showing that a reduction in the stock ratio can have a more pronounced long-term effect than the other two strategies. Therefore, adjusting the investment strategy might be less suitable for mitigating the negative impact of a short-term pandemic event such as COVID-19. Overall, the strategy seems more effective than stopping new business (see Fig. 6) but is more limited than the strategy of increasing premiums (see Fig. 7).¹⁶ Furthermore, reallocating all assets to bonds may not be worthwhile for shareholder value maximization because of the comparably small further risk reduction at the cost of a lower profit potential.

4 Summary

In this study, we examine the effectiveness of different risk mitigation strategies that can be applied on short notice during a pandemic on the basis of a COVID-19 stress test for life insurance. To the best of our knowledge, this study is the first to use an asset-liability model to examine the impact of a joint financial and mortality shock caused by COVID-19 on a life insurer offering annuities and term life insurances. Mortality rates are modeled by an extension of the LC model, where we use mortality data from the first year of the COVID-19 pandemic in Germany (smaller shock) and Spain (larger shock) to embed realistic mortality shocks. Financial shock differs between high- and low-risk investments, increases market and credit risks, and is calibrated to financial data from the first year of the COVID-19 pandemic. The life insurer's asset-liability model accounts for new business (annuity and term life) sold to policyholders of different age groups, actuarial fair premiums, and dividend payments to shareholders. First, we use Monte Carlo simulation to analyze the longand short-term effects of the individual and joint shocks on the life insurer's risk situation under different product portfolios (annuity vs. term life). Second, we investigate the effectiveness of three risk mitigation strategies observed in practice, focusing on a life insurer with a high share of term life insurance. We consider stopping new business for certain age groups, increasing premiums during the pandemic, and adjusting the investment portfolio at the beginning of the pandemic.

The numerical results of our simulation analysis show that financial and mortality shocks can reinforce each other and, therefore, should not be analyzed separately. Product diversification, i.e., selling annuities next to term life insurances, can completely negate the negative impact of the mortality shock but not that of the financial shock. Furthermore, our results indicate that a temporary pandemic event such as COVID-19 might have only a limited impact on the long-term risk situation of life insurers as the increase in one-year default probabilities exponentially decreases immediately after the end of the pandemic in our simulation analysis. Stopping new business during the pandemic reduces the negative impact of the stress scenario; however, its effectiveness is low. Furthermore, we observe that solely excluding policies for older age groups (in anticipation of a larger mortality shock at older ages) is not necessarily beneficial as older policyholders generally carry lower risks due to their shorter duration until death. Premium increases during a pandemic turn out to be a very effective risk mitigation strategy in our stress test as it increases the life insurer's equity, helping to deal with

 $^{^{16}}$ This is also supported by the values of the overall default probabilities given in Table 5 in the Appendix.

the financial and mortality shocks. However, in practice, this strategy bears the risk of losing market position. Adjusting the investment portfolio at the beginning of the pandemic is more effective than stopping sales but leads to more pronounced negative long-term effects owing to the long-term nature of bond investments and might be less suitable for mitigating the risks of a short-term pandemic event such as COVID-19.

In conclusion, our simulation analysis shows that either the applicability in practice or the effectiveness of such immediate measures is limited. Therefore, more sophisticated risk mitigation strategies, such as reinsurance or alternative risk transfer seem unavoidable for life insurers next to product portfolio diversification. While investigating these strategies is beyond the scope of the current study, further research could analyze their effectiveness under a COVID-19 stress test. Additionally, our findings are limited to the impact of COVID-19 on mortality and insurer investment; hence, other aspects such as demand or contract cancellation could also be addressed in future research. Our results also rely on the specific impact of COVID-19 on mortality and financial markets, and such effect may differ in future pandemics. Furthermore, the study does not examine the effectiveness of combining different strategies, which might also be interesting to analyze. Although the greatest impact of COVID-19 appears to be over, the next pandemic will likely occur sooner than expected, and life insurers should be prepared for this situation. Even when specific characteristics differ between pandemics, this study provides some general insights into what to expect and how to respond as a life insurer.

Appendix

See Fig. 9, Tables 3, 4 and 5.



Fig. 9 Estimated parameters a_x and b_x of the LC model for Germany and Spain

Number of sold term life contracts in $t = 10^+$	Age groups	Germany	Absolute decrease	Spain	Absolute decrease
9000	30/40/50	16.11%		19.42%	
6000	40/50	16.07%	-0.04 p.p.	19.40%	-0.02 p.p.
6000	30/50	16.04%	-0.07 p.p.	19.25%	-0.17 p.p.
6000	30/40	15.86%	-0.25 p.p.	19.10%	-0.32 p.p.
3000	50	15.97%	-0.14 p.p.	19.15%	-0.27 p.p.
3000	40	15,81%	-0.30 p.p.	18.98%	-0.44 p.p.
3000	30	15.77%	-0.34 p.p.	18.89%	-0.53 p.p.
0		15.16%	-0.95 p.p.	18.12%	- 1.30 p.p.

Table 3 Overall default probability *DP* when in year t = 10, the joint financial and mortality shock is applied for Germany and Spain under different numbers of sold contracts in $t = 10^+$

Notes: The number of sold contracts is 3000 for all age groups, and the absolute decrease is expressed in percentage points (p.p.)

Table 4 Overall default probability *DP* when in year t = 10, the joint financial and mortality shock is applied for Germany and Spain under different loadings λ in $t = 10^+$

	Germany	Absolute decrease	Spain	Absolute decrease
$\lambda = 0\%$	16.11%		19.42%	
$\lambda = 1\%$	15.45%	– 0.66 p.p.	18.69%	-0.73 p.p.
$\lambda = 2\%$	14.83%	– 1.28 p.p.	17.99%	– 1.43 p.p.
$\lambda = 23\%$	9.04%	– 7.07 p.p.	10.38%	-9.04 p.p.

Notes: The absolute decrease is expressed in percentage points (p.p.)

Table 5 Overall default probability *DP* when in year t = 10, the joint financial and mortality shock is applied for Germany and Spain under different adjusted stock ratios α in $t = 10^+$

	Germany	Absolute decrease	Spain	Absolute decrease
$\alpha = 15\%$	16.11%		19.42%	
$\alpha = 10\%$	15.29%	-0.82 p.p.	18.49%	-0.93 p.p.
$\alpha = 5\%$	15.03%	- 1.08 p.p.	18.11%	– 1.31 p.p.
$\alpha = 0\%$	15.48%	-0.63 p.p.	18.48%	-0.94 p.p.

Notes: The absolute decrease is expressed in percentage points (p.p.)

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Data availability The mortality data used in this study are publicly available in the Human Mortality Database at https://www.mortality.org/. The other data used in this study are available from the author upon reasonable request.

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