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Sensitivity Estimation of Traditional Life BEL Using Regression Proxies

a cura di
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Index

Abstract 5

1 Introduction 5

2 Theoretical background and model specification 8

3 Dataset and definition of explanatory risk factors 13

3.1 Definition of explanatory risk factors 14

4 Empirical Results 18

4.1 Experimental Framework 18

4.2 Specifications 19

4.3 Run of the proxies 20

4.4 Marginal Effects and Sensitivity Analysis 26

4.5 Discussion on market-only vs. full specification, loss absorbing capacity and stress tests. 29

5 Decomposing Balance-Sheet Dynamics: Market Sensitivities vs. Volume Effects in the Estimation of BEL Variations and Orthogonalization of Risk Factors 32

5.1 A Micro-Level Decomposition of Market Value Changes 32

5.2 The Structural Ambiguity of the Risk-Free Curve 37

5.3 Stress Testing Framework and Behavioral Dynamics 41

6 Further extensions and conclusions 43

6.1 Moving Toward Risk-Driver-Based Parametrisation 43

6.2 Conclusions 45

References 48

Quaderni pubblicati 51

Sensitivity Estimation of Traditional Life BEL Using Regression Proxies

Francesco Sciarretta, Francesco Ficarola, Stefano Pasqualini, Silvia Sacco[1, 2]

Abstract

Under the current international regulatory framework, insurance supervisors are mandated to evaluate the resilience of insurers against adverse yet plausible financial shocks. This responsibility applies both at the individual entity level and across the financial system. Such assessments are essential to safeguard stability and support effective macroprudential oversight. This task is especially relevant for insurance liabilities, whose valuation is often highly sensitive to financial market conditions and policyholder behaviour. Under Solvency II, evaluating traditional life Best Estimate Liabilities (BEL) requires capturing complex, path-dependent interactions between assets, liabilities, and embedded policyholder options. While insurance undertakings typically rely on detailed internal models and full stochastic simulations, such approaches are not directly available at the supervisory level, where analyses are based on reporting data. To address these limitations, regression-based proxy models are employed to approximate liability responses through parsimonious statistical relationships with key financial and technical risk drivers.

The framework is designed to assess sensitivities rather than to forecast future BEL levels, providing an analytically tractable tool for instantaneous shock analysis. The work also discusses the construction of market-only specifications, the treatment of embedded policyholder behaviour in observed data, and the implications of scaling shocks beyond historical ranges. The findings highlight the potential of regression proxies to serve as efficient, interpretable and scalable approximations of instantaneous liability movements, particularly in macroprudential analysis and top-down stress testing exercises.

1 Introduction

Under the current international regulatory framework, insurance supervisors are explicitly mandated to assess the resilience of insurers to adverse but plausible financial shocks, both at the individual and at the sector level. This mandate is firmly embedded in the Insurance Core Principles (ICPs) issued by the International Association of Insurance Supervisors (IAIS), and has been further reinforced by recent developments in macroprudential supervision and resolution planning frameworks.

In particular, ICP 24 (Macroprudential Supervision, see IAIS 2024) establishes that supervisors should identify, monitor, and assess systemic risks arising from

1 IVASS, the Institute for the Supervision of Insurance, Supervisory Regulations and Policies Directorate, Macroprudential Analysis Division.

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the insurance sector, including vulnerabilities stemming from market-consistent valuation and the transmission of financial shocks through balance sheets. ICP 24 explicitly requires supervisory authorities to develop analytical tools capable of evaluating the impact of severe market movements on insurers' financial positions, both under normal conditions and under stress. These requirements naturally extend to the assessment of insurance liabilities, especially where valuation is sensitive to financial market dynamics and policyholder behaviour.

The supervisory role in this domain is further developed in the IAIS Application Paper on Macroprudential Supervision (see IAIS 2021), which provides practical guidance for the implementation of ICP 24. Within this framework, Section 3.2 ("Common quantitative analysis methods") emphasizes the importance of developing consistent, scalable, and interpretable analytical techniques that allow supervisors to assess vulnerabilities across the insurance sector as a whole or a significant sub-sample of insurers, according to their exposures to specific risks. More specifically, Section 3.2.2 ("Stress testing") highlights the need for top-down stress-testing methodologies that can be applied flexibly across entities of different sizes and complexities or on the market as a whole, support the analysis of instantaneous and hypothetical scenarios.

Within this institutional context, supervisors face a fundamental operational challenge: the need to evaluate the sensitivity of market-consistent liabilities to a wide range of exogenous shocks across the sector, often under tight time constraints. While full asset-liability simulations represent the benchmark for undertaking-level risk management, they are not available for supervisory analysis.

The accurate estimation of life technical provisions under Solvency II represents a central challenge for insurance undertakings. In traditional life business, the interaction between assets and liabilities is inherently complex and path-dependent, as valuation in a market-consistent framework requires capturing the embedded options and guarantees within policyholders' contracts. In the absence of closed-form solutions, such interactions are typically assessed through stochastic simulations, which are computationally demanding and often impractical when applied to broad scenario sets (EIOPA 2019b, Bauer, Reuss, and Singer 2012, Feng and Volkmer 2012, Anne-Sophie Krah, Zoran Nikolić, and Ralf Korn 2020). To address these challenges, the literature and regulatory guidance have increasingly discussed the use of proxy models, that is, simplified statistical representations linking a target economic variable to a parsimonious set of risk drivers. EIOPA Methodological Paper on Stress Test (see EIOPA 2019b) highlights that, in place of full nested stochastic simulations, regression-based techniques can be used to approximate the variation of liabilities or own funds under different market conditions. Among the various families of proxy approaches, regression-based models, including polynomial regressions, generalized linear or additive models, and other data-driven extensions, provide an interpretable and computationally efficient framework to describe the sensitivity of traditional life

liabilities to selected financial and technical risk factors (see Anne-Sophie Krah, Zoran Nikolić, and Ralf Korn 2020).

This paper examines the intersection between regulatory objectives and data availability by introducing a regression-based proxy framework for traditional life BEL. Rather than projecting future liability levels, the framework focuses on evaluating sensitivities and transmission channels, ensuring consistency with international standards and supporting supervisory authorities in strengthening macroprudential oversight and stress-testing practices. A genuine forecasting exercise would require a fully specified stochastic model describing the dynamic evolution of the underlying risk factors over time, for which the necessary data are not available. In contrast, the present approach focuses on scenario-based sensitivity analysis, quantifying how BEL would adjust to hypothetical shocks at a given point in time. To this end, the framework does not simulate risk-factor trajectories, but relies on observed balance-sheet variables as empirical proxies for the realised states of the underlying stochastic processes. Asset allocations, premiums, claims, and expenses are thus interpreted as observable accounting counterparts of otherwise latent economic drivers. While this approach offers a more data-driven alternative to scenario generation, it may introduce challenges related to aggregation, endogeneity, and stability over time. These issues require careful validation, particularly because quarterly changes in entities' balance sheets embed a volume component that is mechanically linked to movements in BEL. These variables, however, embed the company's exposure to underlying market and behavioral risks, making them a meaningful basis for approximating liability sensitivities.

This work adopts a sector wide perspective, focusing on the insurance market as a whole rather than on individual undertakings. This distinction is essential as the authors do not have access to firms' granular contract-level data, and therefore the model cannot be interpreted as a best practice or replicable template for companies' internal use.

The remainder of the paper is structured as follows. Section 2 reviews the main regression-based proxy techniques and relates them to the methodological principles of insurance stress testing. Section 3 describes the supervisory dataset and the construction of the explanatory variables used to approximate quarterly changes in BEL. Section 4 presents the empirical results, including model comparison, validation exercises, marginal-effects analysis and discusses the interpretation and limitations of the baseline specification. Section 5 refines the framework for supervisory stress-testing purposes by decomposing asset variations into price and volume components, orthogonalizing fixed-income risk factors, and showing how the resulting specifications can be applied to instantaneous stress scenarios. Section 6 concludes and outlines possible extensions toward a fully risk-driver-based framework.

2 Theoretical background and model specification

The methodological framework described by EIOPA in Section 5.4.3 of the Insurance Stress Test Methodology (see EIOPA 2019b) was developed in analogy with undertakings' internal model practices, where proxy models (LSMC, replicating portfolios, or curve-fitting) are used to avoid full nested stochastic simulations under hypothetical stress conditions. Although these approaches help overcome the computational burden of nested stochastic simulations, their implementation and validation remain methodologically intricate and operationally demanding for insurers, and are not directly applicable in a supervisory context. While a full recalibration of regression models after each stress scenario would be the most accurate approach, it is rarely feasible within the tight timelines of stress-testing exercises for insurers and is further constrained in a supervisory context by the lack of granular data and model access. For instance, in the EIOPA 2018 stress test, some approximations were explored, such as scaling the loss distribution generated under the baseline by applying specific post-stress sensitivities (see EIOPA 2019b).

The evaluation of the appropriateness and plausibility of the approximations should be a core element of the validation process, both within undertakings and by supervisory authorities.

The underlying assumption of the general framework is that risk drivers are simulated, typically within a stochastic economic scenario generator (ESG), and that the proxy function should therefore approximate the behavior of BEL or own funds across a multidimensional set of simulated market scenarios (e.g. Krah et al., 2019). In this setting, simulation of risk factors is a necessary step, because the model must learn the functional relationship (1) between the economic variable of interest Y and drivers X from a sufficiently rich space of synthetic risk factor paths:

$$f(X) = \mathbb{E}[Y|X] \tag{1}$$

The present work shares the same conceptual structure, but introduces a simplification that can be particularly suited for a sector-wide or supervisory application, when the goal is to assess the instantaneous response on Y and the shocks on X are already given.

Instead of relying on simulated risk factor scenarios, this work uses the historical series of realized market and technical factors as the empirical basis for calibration. This approach replaces the synthetic risk factor variation generated by the ESG with observed cross-sectional and temporal variation in the main balance-sheet components of insurance companies.

In other words, while the LSMC framework estimates the function (1), where X represents both market and actuarial drivers and Y denotes modelled BEL, the current approach estimates the same mapping using realised data. The interpretation remains identical, as the regression function represents the empirical sensitivity of BEL to changes in the relevant market and technical drivers, but requires careful feature engineering to capture risk sensitivities and may call for more flexible machine learning techniques to handle non-linearities and heteroscedasticity. Validation becomes critical to ensure that these proxies generalize across time and stress conditions, given their potential aggregation and endogeneity issues.

Although simplified, the model remains consistent with the conceptual logic of proxy modelling under Solvency II. The observed changes in the composition of assets and in technical flows embody both the effects of market movements, management actions and policyholder behavior. Therefore, these empirical variations provide an observable real-world manifestation of the same risk dynamics that stochastic proxy models are designed to approximate.

The resulting function can then be used to produce sensitivity and attribution analysis, parametric stress testing or plausibility checks within the authority's analytical toolkit.

Eight models are considered:

(1) Ordinary Least Squares (OLS). The starting point of the regression framework is the Ordinary Least Squares model, which assumes a linear relationship between the dependent variables **Y** and a matrix of explanatory variables **X**:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \varepsilon. \tag{2}$$

The OLS estimator **b**, is computed as:

$$\mathbf{b} = (\mathbf{X}^\top \mathbf{X})^{-1}\mathbf{X}^\top \mathbf{Y} \tag{3}$$

This method provides BLUE (Best Linear Unbiased Estimates) $\hat{\beta}$ under Gauss Markov assumptions. In BEL modeling, OLS serves as a benchmark proxy, quantifying the average sensitivity of liabilities to small asset-side variations. However, it is sensitive to heteroskedasticity and outliers, also it cannot capture non-linear or interaction effects.

(2) Generalized Linear Model (GLM) and Quasi-GLM. The Generalized Linear Model (see Nelder and R. W. M. Wedderburn 1972) extends OLS by allowing the conditional mean of Y to depend on a link function g(·) of the linear predictor:

$$\mathbb{E}[\mathbf{Y}|\mathbf{X}] = g^{-1}(\mathrm{X}\boldsymbol{\beta}) \tag{4}$$

where $g(\cdot)$ is a monotonic differentiable function and the distribution of **Y** belongs to the exponential family. GLMs are especially relevant in actuarial contexts, where variables often exhibit heteroskedastic or asymmetric distributions. By explicitly modeling the mean-variance relationship through the variance function $\mathbb{V}ar(\mathbf{Y}|\mathbf{X}) = \phi V(\mu)$, GLMs generalize OLS while maintaining interpretability and closed-form estimation and are easy to extend to quasi-likelihood methods. However, it still assumes a specific mean-variance relationship and may not handle extreme outliers.

When the distribution of the residuals deviates from the exponential family – e.g., when heteroskedasticity or serial correlation is present – the Quasi-Likelihood (Quasi-GLM) framework could be used (see R. Wedderburn 1974). This approach retains the link function $g(\cdot)$ but does not assume any specific distribution for Y. Instead, it defines a pseudo-likelihood based only on the first two moments:

$$\mathbb{E}[\mathbf{Y}|\mathbf{X}] = \mu, \quad \mathbb{V}ar(\mathbf{Y}|\mathbf{X}) = \phi V(\mu) \tag{5}$$

Parameter estimates are obtained by solving the quasi-score equations, yielding consistent but not necessarily efficient estimates. In practice, Quasi-GLMs correct the standard errors for model misspecification, and thus provide more reliable inference when the true variance structure of BEL changes is unknown or irregular.

(3) Polynomial Regression (POLY). To capture potential non-linearities without departing from the regression framework, Polynomial Regression augments the linear model by including higher-order terms of the explanatory variables (see Gergonne 1815). For a generic dependent variable Y , with predictors x1, ..., xk, a polynomial regression of degree d, without interaction terms, is computed as:

$$\mathbb{E}[Y|X] = \beta_0 + \sum_{j=1}^{k} \sum_{l=1}^{d} \beta_{j,l} x_j^l \tag{6}$$

This specification approximates smooth, continuous non-linear relationships between asset-side factors and the variation in BEL through Taylor expansions of low degree (typically 2nd or 3rd order). In the current context, the quadratic specification allows for convex or concave reactions of BEL to market shocks-e.g., non-linear sensitivity to large bond yield movements or equity drawdowns. It retains interpretability and analytical form and can approximate mild curvature.

(4) Robust Linear Model (RLM). The Robust Linear Model is designed to mitigate the influence of outliers or heavy-tailed residuals that can bias OLS estimates. Instead of minimizing squared residuals, RLM minimizes a robust loss function $\rho(\varepsilon_t)$, such as the Huber or Tukey biweight function:

$$\hat{\boldsymbol{\beta}} = \min_{\beta} \sum \rho\left(\frac{\mathbf{Y} - \mathbf{X}\boldsymbol{\beta}}{s} \right), \tag{7}$$

where *s* is a robust scale estimate. This approach downweights extreme residuals, yielding estimates that are less sensitive to aberrant observations or reporting anomalies – conditions that can be encountered in Solvency II data due to firm-specific events. In estimating sectoral BEL, RLM ensures that extreme BEL changes from individual undertakings do not disproportionately affect the fitted relationship between liabilities and risk factors.

(5) Feasible Generalized Least Squares (FGLS). In many macro-financial datasets, residuals exhibit heteroskedasticity or autocorrelation across time or entities. The Feasible Generalized Least Squares (FGLS) estimator corrects for these issues by transforming the regression to account for a non-spherical covariance structure of the errors (see Bai, Choi, and Liao 2020):

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \varepsilon, \quad \mathbb{V}ar(\varepsilon) = \sigma^2 \Omega \tag{8}$$

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^\top \hat{\boldsymbol{\Omega}}^{-1} \mathbf{X})^{-1} \mathbf{X}^\top \hat{\boldsymbol{\Omega}}^{-1} \mathbf{Y} \tag{9}$$

where $\hat{\boldsymbol{\Omega}}$ is an estimate of the error covariance matrix. In practice, the model is estimated in two stages: first, residuals from an OLS fit are used to estimate $\hat{\boldsymbol{\Omega}}$; second, the regression is re-estimated with weighted least squares. In this application, FGLS provides a way to account for cross-sectional heterogeneity and time correlation among insurers' balance sheets, preserving a linear structure. It improves efficiency when the residual variance depends systematically on the magnitude of shocks or on the company's scale. However, it requires the correct specification of $\boldsymbol{\Omega}$, and estimation noise may reduce small-sample performance.

(6) Generalized Additive Model (GAM). The Generalized Additive Model (see T. Hastie and R. Tibshirani 1986) introduces flexibility by replacing linear terms with smooth functions $s_j(\cdot)$, estimated non-parametrically:

$$\mathbb{E}[Y|X] = s_0 + \sum_{j=1}^{k} s_j(x_j) \tag{10}$$

Each s_j is a data-driven function capturing non-linear, yet smooth and interpretable, effects of the explanatory variable on the dependent variable. GAMs can thus reveal gradual curvature, saturation, or asymmetric sensitivities without assuming a specific form. They strike a balance between linear transparency and machine-learning flexibility.

(7) Kernel Regression (KERNEL). Kernel Regression (also known as Nadaraya-Watson regression) estimates the conditional mean of *Y* given *X* without assuming any functional form:

$$\mathbb{E}[Y|X] = m(X) \tag{11}$$

$$\hat{m}(x) = \frac{\sum_i K_h(x - x_i) y_i}{\sum_i K_h(x - x_i)} \tag{12}$$

where $K_h(\cdot)$ is a kernel function (typically Gaussian or Epanechnikov) with bandwidth *h*. The bandwidth controls the degree of local averaging, where small *h* yields more flexibility, while large *h* smooths the curve. Kernel methods offer a fully non-parametric alternative to regressions, capturing local nonlinearities in a data-driven way. In insurance applications, they can approximate local sensitivities of BEL to market shocks without imposing a global structure.

(8) Regularized Regression: LASSO, Ridge, and Elastic Net. To mitigate overfitting and improve variable selection in high-dimensional or collinear settings, regularized regression estimators are employed to augment the ordinary least squares criterion with a penalty on the magnitude of coefficients. The general framework solves:

$$\min_{\boldsymbol{\beta}} \left\{ \sum_{i=1}^{n} (y_i - \mathbf{x}_i' \boldsymbol{\beta})^2 + \lambda P(\boldsymbol{\beta}) \right\} \tag{13}$$

where $P(\boldsymbol{\beta})$ is a penalty function and $\lambda \geq 0$ controls the strength of regularization.

In the Ridge regression estimator (see Hoerl and Kennard 1970), the penalty is quadratic,

$$P_{\text{Ridge}}(\boldsymbol{\beta}) = \|\boldsymbol{\beta}\|_2^2 = \sum_{j=1}^{k} \beta_j^2 \tag{14}$$

which shrinks coefficients toward zero but does not set any of them exactly to zero. Ridge thus stabilizes estimates under multicollinearity, improving predictive performance but not performing variable selection.

The Least Absolute Shrinkage and Selection Operator (LASSO) introduced by Tibshirani (see Robert Tibshirani 1996) instead applies an L_1-norm penalty,

$$P_{\text{LASSO}}(\boldsymbol{\beta}) = \|\boldsymbol{\beta}\|_1 = \sum_{j=1}^{k} |\beta_j| \tag{15}$$

which induces sparsity in the estimated parameter vector. By forcing some coefficients exactly to zero, the LASSO simultaneously performs estimation and variable selection, yielding a parsimonious model that retains only the most relevant predictors. While LASSO is well-suited for feature selection, it may be

unstable when predictors are highly correlated. To address this, Elastic Net regularization (see Zou and Trevor Hastie 2005) combines both penalties:

$$P_{\mathrm{EN}}(\boldsymbol{\beta}) = \alpha\|\boldsymbol{\beta}\|_1 + (1-\alpha)\|\boldsymbol{\beta}\|_2^2, \quad \alpha \in [0,1] \tag{16}$$

The Elastic Net interpolates between Ridge (α=0) and LASSO (α=1), balancing variable selection and coefficient shrinkage.

For approaches of FGLS, ridge and robust regression in life insurance proxy modeling, see also Hartmann 2015, A.-S. Krah 2015 and Z. Nikolić, Jonen, and Zhu 2017, respectively. In analogy with Castellani et al. 2018, Kopczyk 2018, Schelthoff 2019 and Schoenenwald 2019, additional estimations were conducted using machine learning algorithms, namely Random Forest and Extreme Gradient Boosting, to test whether the relationship between changes in BEL and asset-side factors could exhibit relevant non-linearities or interaction effects. However, these models displayed substantially weaker out-of-sample performance compared with the linear and semi-parametric specifications and thus are not shown here for brevity. This outcome mainly reflects the limited size of the dataset (see Section 3), the strong co-movement among financial variables, and the relatively low signal-to-noise ratio in quarterly liability variations. In this context, tree-based algorithms tend to overfit or converge toward nearly constant predictions. Linear proxy models therefore provide a more robust and interpretable framework for sector-wide sensitivity analysis.

The analysis does not rely on panel or time-series econometric specifications with fixed or random effects, as the objective of the study is not to model the dynamic evolution of liabilities over time as already discussed. For this reason, the variables are expressed in relative changes to ensure comparability across undertakings. This transformation reduces persistence and firm-specific level effects, allowing the regression framework to approximate a cross-sectional relationship between liability variations and contemporaneous market movements.

3 Dataset and definition of explanatory risk factors

The empirical analysis is based on quarterly supervisory reporting data submitted by 36 individual life and composite insurance undertakings from the first quarter of 2016 to the second quarter of 2025. Four templates are exploited as main data sources in this paper: Balance Sheet and Premiums, Claims and Expenses by Line of Business for results in Section 4, the List of Assets for Section 5 and Life and Health SLT Technical Provisions for both Sections 4 and 5. These templates provide

a consistent, Solvency II-compliant view of the balance-sheet for both individual undertakings and, through aggregation, for the insurance sector as a whole.

The analysis focuses exclusively on traditional life (with-profit) business, for which BEL are reported at each quarter-end. Rather than modelling the absolute level, the framework examines their quarter-on-quarter relative variation. Expressing BEL changes in relative terms ensures comparability across under-takings of different sizes, placing entities on a homogeneous scale and allowing for meaningful cross-sectional analysis.

The dependent variable of the regression framework is therefore the relative change in BEL, denoted as ΔBEL, computed as:

$$\Delta BEL = \frac{BEL_t - BEL_{t-1}}{BEL_{t-1}} \tag{17}$$

for each individual undertaking. The market aggregate is constructed consistently by first summing the individual BEL levels across undertakings at each date and then computing the corresponding relative quarter-on-quarter change from the aggregated series.

3.1 Definition of explanatory risk factors

Two broad categories of explanatory variables are considered: market-related drivers and technical-accounting drivers. In addition, a measure capturing changes in the EIOPA risk-free curve is included to reflect the direct sensitivity of the present-value computation of BEL under SII.

From the balance-sheet template, quarterly relative changes in asset values for the main investment classes held by life insurers are extracted. Specifically, the following rows are used:

- Government bonds (ΔGov)
- Corporate bonds ($\Delta Corp$)
- Collective Investment Undertakings (ΔCIU)
- Equity instruments ($\Delta Equity$)

Then are considered the relative changes in quarterly flow variables: premiums, claims and expenses relevant to the traditional life line of business:

- Gross premiums written ($\Delta Premia$)
- Gross claims incurred ($\Delta Claims$)
- Expenses incurred (ΔExp)

These variations capture the technical evolution of the portfolio over time and complement the market drivers in explaining liability changes.

From the List of Assets, all the lines of investments have been assessed at ISIN level, taking into account all the columns of the template useful to address both the price and the volume change effects on the total market value change of a generic asset (see relative EIOPA's Implementing Technical Standards):

- Percentage of par;
- Unit price;
- Par amount;
- Quantity;
- Accrued interest;
- SII amount;
- Residual modified duration;
- Maturity date.

Finally, change in risk-free rate is measured at the point corresponding to the duration of liabilities of the undertaking *i*:

$$\Delta r_t = r_t(D_i) - r_{t-1}(D_i) \tag{18}$$

where $\Delta r_t(D_i)$ denotes the risk-free rate at maturity D for the undertaking i at quarter t. This term serves as a synthetic indicator of the shift in market evaluation of BEL.

For each quarter *t* and undertaking *i*, the full dataset therefore consists of a vector of explanatory variables:

$$\mathbf{X}_{i,t} = \begin{pmatrix} \Delta Gov_{i,t},\ \Delta Corp_{i,t},\ \Delta Equity_{i,t},\ \Delta CIU_{i,t}, \\ \Delta Premia_{i,t},\ \Delta Claims_{i,t},\ \Delta Exp_{i,t},\ \Delta r_t(D_i) \end{pmatrix} \tag{19}$$

The table summarizes the historical variability of the dependent variable and of the main drivers used in the proxy framework. The descriptive statistics for the aggregate market variations highlight several relevant features of the Italian life insurance sector over the sample period (see Table 1). Overall, the average relative variation in BEL is slightly positive, reflecting a life insurance market that has continued to expand over time. However, within a market-consistent valuation framework, changes in interest rates play a crucial role in determining the present value of liabilities. In particular, increases in risk-free rates mechanically reduce the

present value of future liability cash flows, an effect that is especially pronounced for undertakings characterized by relatively long liability durations.

Table 1

Descriptive statistics of quarterly changes in BEL and explanatory variables for the Italian life insurance market aggregate (2016Q2-2025Q2)

Variable	*Mean*	*Median*	*Std. Dev.*	*Min*	*Max*
Δ***BEL***	0.2%	0.2%	3.1%	-8.6%	7.4%
ΔGov	-0.1%	-0.5%	4.0%	-9.4%	10.0%
ΔCorp	0.4%	0.5%	2.9%	-7.7%	6.1%
ΔCIU	1.9%	2.1%	3.9%	-5.9%	10.7%
ΔEquity	1.4%	1.2%	7.7%	-19.4%	21.8%
Δr(*D*)	0.1%	0.0%	0.4%	-0.9%	1.1%
ΔPremia	0.4%	-3.5%	15.3%	-22.1%	34.4%
ΔExpenses	2.1%	-2.9%	20.4%	-35.5%	85.9%
ΔClaims	3.8%	0.3%	21.7%	-27.7%	58.7%
Observations (2016Q2-2025Q2)			37		

The largest negative quarterly relative change in BEL, equal to 8.6%, was observed between March and June 2022. This period coincided with the first significant increases in risk-free reference rates following the outbreak of the war in Ukraine and the subsequent surge in inflation. In response to rising inflationary pressures, major central banks tightened monetary policy by raising policy rates and progressively withdrawing accommodative measures. The resulting upward shift in the interest rate environment led to a marked decline in the market value of several financial assets. In the same period, government bonds recorded a decrease of approximately 9.4%, corporate bonds declined by about 7.7%, and funds fell by roughly 5.9%, representing the largest negative quarterly relative variations observed for these asset classes within the sample.

Conversely, the largest positive quarterly variation in BEL, equal to 7.4%, was recorded between December and September 2023, reflecting a phase of partial market adjustment and stabilization following the initial shock associated with the abrupt change in the interest rate environment.

On average, government bonds held in insurers' portfolios appear relatively stable over the sample period. The descriptive statistics indicate a marginal average decline of around 0.1% between quarters. This slight decrease partly reflects the contemporaneous increase in interest rates, which rose on average by approximately 0.1 percentage points from one quarter to the next, exerting downward pressure on bond valuations. By contrast, all other asset categories exhibit positive average growth rates between quarters. In

particular, corporate bonds, equity, funds, as well as premiums, claims and expenses display positive mean variations over the sample period.

Looking at the largest quarterly changes, the most significant appreciation in the value of government bonds held in insurers' portfolios occurred between September and December 2023. For corporate bonds, the largest positive quarterly change was observed between March and June 2020. It is worth noting that this increase followed a sharp decline of about 5% recorded in March 2020 relative to the end of 2019, largely reflecting the market disruption caused by the outbreak of the COVID-19 pandemic.

With regard to investment in funds, the largest quarterly expansion dates back to the early part of the sample, between June and September 2016. However, it should be noted that the total amount invested in CIU at that time was significantly smaller than in recent years-roughly half of current levels. The corresponding quarterly increase therefore amounted to approximately EUR 6 billion, which, while sizeable in relative terms, occurred on a considerably smaller investment base.

Finally, premiums, expenses and claims display higher volatility in their quarterly variations. This partly reflects the fact that these quantities are considerably smaller in absolute terms compared with asset portfolio components. Moreover, their dynamics are influenced by cyclical and seasonal factors, and their fluctuations cannot always be attributed solely to inflationary effects on expenses or to changes in guarantees and market conditions affecting claims. Instead, these variables reflect a combination of operational dynamics, portfolio composition effects and broader developments in the life insurance business cycle.

Table 2

Correlation matrix of the explanatory variables across the full panel of undertakings

	ΔBEL	*ΔGov*	*ΔCorp*	*ΔCIU*	*ΔEquity*	*Δr(D)*	*ΔPremia*	*ΔExp*	*ΔClaims*
Δ*BEL*	1.00	0.17	0.01	-0.01	-0.00	-0.04	0.11	0.00	0.00
ΔGov	0.17	1.00	0.02	-0.05	0.01	-0.32	0.22	0.01	0.01
ΔCorp	0.01	0.02	1.00	0.04	0.00	-0.01	0.02	0.00	0.00
ΔCIU	-0.01	-0.05	0.04	1.00	-0.00	0.01	0.01	0.00	0.00
ΔEquity	-0.00	0.01	0.00	-0.00	1.00	-0.00	-0.00	0.00	-0.00
Δr(*D*)	-0.04	-0.32	-0.01	0.01	-0.00	1.00	-0.05	0.01	-0.00
ΔPremia	0.11	0.22	0.02	0.01	-0.00	-0.05	1.00	0.43	0.02
ΔExpenses	0.00	0.01	0.00	0.00	0.00	0.01	0.43	1.00	0.00
ΔClaims	0.00	0.01	0.00	0.00	-0.00	-0.00	0.02	0.00	1.00

Table 2 reports the correlation matrix of the explanatory variables computed on the full panel of insurance undertakings. Overall, correlations are generally low, suggesting the absence of severe multicollinearity issues in the regression

framework. The largest correlation is observed between changes in premiums and expenses (0.43), which is economically intuitive given the operational linkage between business volumes and administrative costs. A moderate and intuitive negative correlation (-0.32) appears between changes in government bond assets, valued at market value and the change in the risk free rate at liabilities' duration.

For simplicity, the variation of asset classes includes both the price and the volume effect and is thus taken from Balance Sheet reporting template when is experimented the framework described in Section 4. In Section 5 the price-volume decomposition will be addressed. The modeling objective is to approximate the quarterly relative variation in life with-profit BEL as a function of these explanatory factors:

$$\Delta BEL_i = Y_i = f(X_i) + \varepsilon_i \tag{20}$$

where $f(\cdot)$ represents a function estimated under different assumptions regarding linearity, distribution, and variance structure.

4 Empirical Results

4.1 Experimental Framework

The empirical analysis is conducted on quarterly Solvency II data for 36 Italian life and composite insurance undertakings and on the market aggregate, covering the period from 2016Q2 to 2025Q2. For each entity *i*, the dependent variable represents the quarterly variation in BEL, while the explanatory regressors capture both balance sheet and technical liquidity variations. All the models are estimated on an entity-by-entity basis, ensuring full heterogeneity across undertakings, with the Insurance Market entity representing the market aggregate.

Three complementary empirical exercises are implemented:

1. **Full in-sample estimation**, using all quarterly observations (2016Q2 to 2025Q2), to assess overall explanatory power;

2. **Fixed Out-of-Sample evaluation**, where training data include all observations up to 2023Q4 and predictions are computed for 2024Q1 to 2025Q2;

3. **Rolling-window forecasts**, with a training window of 30 quarters and a 4-quarter forecasting horizon, rolling forward over three periods to evaluate temporal stability.

This structure provides complementary evidence on both within-sample fit and out-of-sample forecast accuracy under changing market and interest-rate environments.

Before any model estimation, each training sample undergoes a LASSO variable selection procedure to prevent overfitting and multicollinearity. For each company the penalized least-squares problem is solved (see eq. 13 and 15); where λ is selected through cross-validation, repeated for 100 times in each exercise and the median is chosen. This automatic shrinkage forces some coefficients to zero, yielding a parsimonious subset of predictors X_j retained for subsequent estimation. The variable selection step is repeated within each rolling window, ensuring that the model space evolves endogenously over time as new data become available. The LASSO pre-selection step is implemented uniformly across all modeling frameworks, thereby allowing for direct comparability of results across linear, robust, semi-parametric, and regularized specifications.

4.2 Specifications

Eight models are estimated on each training sample (see Section 2):

1. **OLS:** ordinary least squares;
2. **GLM:** a standard generalized linear model with exponential family Gaussian and identity link;
3. **RLM:** a robust linear model to mitigate the influence of outliers;
4. **FGLS:** feasible generalized least squares including a company-specific AR(1) correlation structure,

$$\varepsilon_{i,t} = \rho_i \varepsilon_{i,t-1} + u_{i,t}, \quad u_{i,t} \sim \text{i.i.d.}(0, \sigma^2),$$

   to account for serial correlation in the residuals;
5. **GAM:** a generalized additive model where each $s_j(\cdot)$ is a smooth spline term;
6. **POLY:** a polynomial expansion up to second order for each regressor;
7. **KERNEL:** nonparametric Nadaraya-Watson kernel regression with cross-validation bandwidth;
8. **ENET_POLY:** an Elastic-Net regression on a second-order polynomial basis with mixed effects and $\alpha = 0.5$.

This comprehensive set of models spans from classical linear regression to flexible nonlinear and regularized specifications, thereby providing a benchmark across diverse paradigms.

Note: Items (1) and (2) are equivalent (see 4.3).

4.3 Run of the proxies

ΔBEL, can take both positive and negative values and is approximately centered around zero. Under these conditions, the Gaussian specification with identity link is the natural choice within the GLM framework. Consequently, OLS, GLM, and quasi-likelihood model with constant variance function $\text{Var}(Y) = \phi$ (any variance proportional to μ or other powers of μ is numerically unstable or undefined) lead to identical coefficient estimates.

Residual diagnostics reveal mild serial correlation at lag 1 in several undertakings, as shown by the autocorrelation function of the GLM residuals, not reported for brevity. To account for this feature, the FGLS is estimated, allowing for an AR(1) correlation structure within each undertaking.

For each undertaking i and model m, model performance is evaluated using the in-sample R^2 as a measure of explanatory power and the RMSE, computed both fixed out-of-sample and rolling window out-of-sample, as an indicator of predictive accuracy. Additional diagnostic statistics are collected, but not reported here for brevity.

Full In-Sample Results. The in-sample results indicate consistently high explanatory power across insurers. Most specifications achieve R^2 values above 0.90, with the GAM, POLY and KERNEL models reaching near-perfect fits in several cases. However, the very high R^2 values should be interpreted with caution given the short time series and the higher risk of overfitting in more flexible models. The RLM and FGLS frameworks deliver performance broadly comparable to the standard GLM, although the FGLS specification improves residual autocorrelation diagnostics. They yield moderately high mean R^2 (0.82-0.85), but with notable variation. GAM attains particularly high in-sample fit; it achieves the highest mean ($R^2 = 0.95$), indicating superior ability to capture non-linear patterns in the data and suggesting strong model fit across most insurers. While this flexibility captures local curvature in the relationship between shocks and BEL, it may also increase the risk of overfitting in relatively small samples. A similar pattern emerges for KERNEL, that exhibits low SD (0.11) in R^2 with a narrower range, implying more consistent performance. However, this flexibility comes at the cost of interpretability and may lead to reduced stability in out-of-sample forecasts, particularly when the sample size is limited. Moreover, both GAM and KERNEL suffer from the exhaustion of degrees of freedom due to their high parameter density relative to the small dataset. POLY also performs well (mean $R^2 = 0.90$), reflecting the benefit of flexible functional forms. Combined with the preliminary LASSO selection of relevant regressors, the inclusion of quadratic terms allows the model to capture moderate nonlinearities – such as convex responses of BEL to yield shocks – while limiting the variance typically associated with fully nonparametric methods. This balance between flexibility and structure makes the polynomial approach a practical compromise for entity-level modeling with relatively short time series (see Figure 1).

Figure 1

Distribution of in-sample R2 across undertakings by model specification (2016Q2–2025Q2)

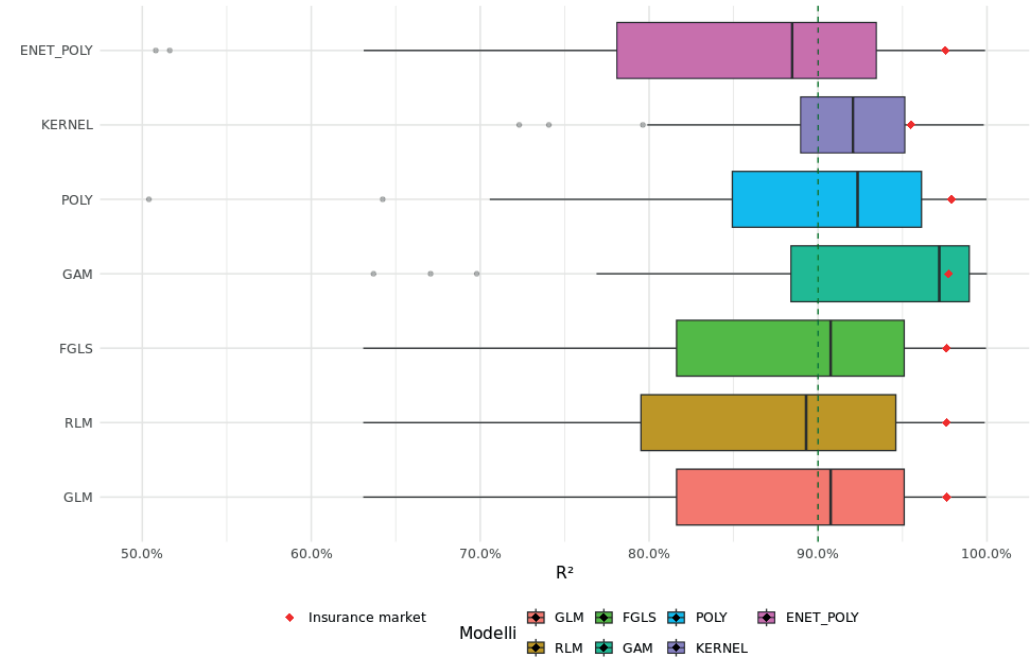


Table 3 reports descriptive statistics of the estimated coefficients linking variations in asset classes and technical cash-flows to changes in BEL across insurers

Table 3

Cross-sectional distribution of estimated GLM coefficients across undertakings

Coefficient	*Mean*	*SD*	*Median*	*Min*	*Max*	*Skew*	*Kurtosis*
β_{gov}	0.36	0.22	0.34	-0.04	0.85	0.35	-0.62
β_{corp}	0.18	0.16	0.16	-0.02	0.61	0.91	0.20
β_{ciu}	0.04	0.06	0.02	-0.04	0.19	0.95	-0.17
β_{equity}	0.02	0.08	0.00	-0.10	0.46	4.14	19.00
$\beta_{r(D)}$	-3.21	2.55	-3.02	-7.69	2.29	0.15	-0.81
β_{prem}	0.01	0.01	0.01	-0.01	0.06	2.13	4.69
β_{exp}	0.00	0.01	0.00	-0.03	0.03	0.03	2.61
β_{claims}	-0.01	0.01	0.00	-0.02	0.02	0.48	-0.24

(only for the GLM for brevity). The results highlight that interest rate sensitivity is the dominant driver of BEL dynamics. The coefficient associated with the discount rate ($\beta r_{(D)}$) displays the largest magnitude (mean = -3.21), consistent with the economic mechanism whereby increases in the discount rate significantly

reduce the present value of liabilities. The relatively large standard deviation (2.55) suggests substantial heterogeneity across insurers, likely reflecting differences in liability duration and product mix. Among asset-side variables, government bond exposures exhibit the largest positive sensitivity (mean β_{gov} = 0.36), followed by corporate bonds (β_{corp} = 0.18). This pattern indicates that changes in fixed-income valuations are systematically associated with BEL variations, possibly through asset-liability interactions and balance-sheet management strategies. In contrast, the coefficients associated with equity and CIU exposures are smaller on average, although the distribution of β_{equity} is highly skewed (skewness = 4.14; kurtosis = 19.0), indicating that equity effects are concentrated in a limited number of insurers with more pronounced market exposure. Coefficients related to technical cash flows (premiums, expenses, and claims) are close to zero on average and display limited dispersion. This suggests that, within the considered framework, short-term variations in technical flows contribute marginally to BEL fluctuations compared with market-driven valuation effects. Also they are already partially covered in the volume variation of the asset class (see section 5).

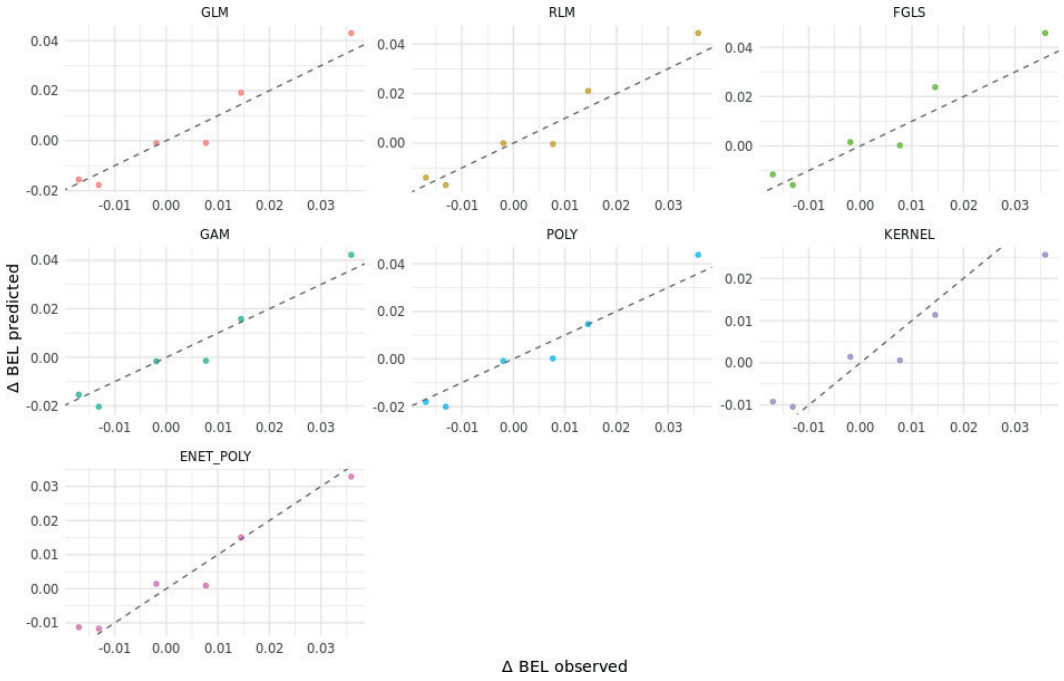
Fixed Out-of-Sample (2024Q1–2025Q2). The fixed out-of-sample experiment is conducted by estimating the models on data up to 2023Q4 and evaluating their predictive performance over the period 2024Q1-2025Q2. Across specifications, the RLM and the POLY models deliver the most stable performance. The robust regression achieves this by down-weighting extreme observations, thereby limiting the influence of idiosyncratic shocks that may otherwise distort parameter estimates. The polynomial specification performs well due to its parsimonious extension of the linear framework, allowing for moderate nonlinearities.

The ENET_POLY achieves the lowest prediction error for the market aggregate, with an average forecasting error of approximately 0.5% over the eighteen-month evaluation horizon. By contrast, the FGLS specification, despite performing well in-sample, tends to deteriorate out-of-sample. This behaviour is consistent with the instability of the estimated AR(1) parameter $\rho_{t'}$, which may vary between the training and testing periods. More flexible approaches such as KERNEL and GAM exhibit higher volatility in their forecasts. While these models achieve very high in-sample fit, their greater flexibility appears to reduce predictive stability when applied to unseen data. Overall, all models achieve relatively low RMSE levels, indicating that the regression proxies provide an accurate approximation of BEL dynamics at the aggregate level. Coefficients among models are consistent with the in-sample fit, with very small variance, also thanks to LASSO pre-selection, and are not shown here for brevity.

Figure 2 illustrates the relationship between observed and predicted variations in BEL for the market aggregate. All models broadly capture the direction of BEL adjustments, but the amplitude of predicted responses varies.

Figure 2

Observed and predicted quarterly changes in BEL for the insurance market aggregate: fixed out-of-sample evaluation (2024Q1–2025Q2)



A mild attenuation pattern is visible for the largest positive BEL variations, which tend to be slightly underpredicted. This behaviour is consistent with the smoothing properties of regression-based proxy functions when approximating highly non-linear valuation responses. In these cases POLY and ENET thanks to greater flexibility capture better the non linearity response. Importantly, all models correctly capture the sign of BEL adjustments across the evaluation sample, indicating high directional accuracy. This property is particularly relevant in supervisory applications, where correctly identifying the direction of liability revaluations is often more informative than minimizing small prediction errors.

Rolling-Window Forecasts. Rolling-window analysis was implemented to assess model stability and out-of-sample forecasting performance across short forward horizons and moving training windows. This design assesses temporal stability and sensitivity to structural changes. Three training windows of fixed length of 30 quarterly observations and a fixed forecast horizon of four quarters are used. Concretely, for each insurer the algorithm performs up to three consecutive rolling estimates with index $start_i = 1, 2, 3$. For a generic $start_i$ the training and test indices are:

- $train_{idx} = start_i : (start_i + 29)$
- $test_{idx} = (start_i + 30) : (start_i + 33)$,

Table 4

Rolling-window train–test design used for the temporal stability analysis

e.g.	Train period	Test period
1	2016Q2–2023Q4	2024Q1–2024Q4
2	2016Q3–2024Q1	2024Q2–2025Q1
3	2016Q4–2024Q2	2024Q3–2025Q2

For each window, a LASSO-based variable pre-selection step is performed first on the window's training observations, then using only the selected variables, all the model specifications in 4.2 are fitted on the training window. For each model, window and undertaking, are computed and stored prediction, performance metrics and selected variables list. Intercepts are removed and absolute coefficients are used to compute a per-model, per-window Relative Importance:

$$RelativeImportance_j = \frac{|\beta_j|}{\sum_k |\beta_k|} \tag{21}$$

The collected coefficient panel enables plots of rolling betas and the evaluation of parameter stability across windows; results are not shown for brevity. Considering the small sample available, a smaller training length would have resulted in problems with the LASSO pre-selection that requires at least 3 folds to estimate in cross validation the optimum λ. This rolling-forward experiment therefore provides a time-resolved view of coefficient stability, and a collection of windowed variable selections that together inform model robustness and interpretability.

The panel of Figure 3 highlights the substantial increase in volatility under the rolling-window design, with RMSE distributions extending up to 4 – 5%. This reflects the sensitivity of models to structural changes and the limited sample size within each training block. Specifications such as KERNEL and GAM exhibit the widest spreads and highest upper tails, confirming their tendency to overfit local patterns and potential loss of generalization capacity when regimes shift. In contrast, regularized approaches like ENET_POLY maintain relatively stable performance, although with greater dispersion compared to the fixed out-of-sample experiment. Similarly, GLM, RLM, and POLY stand out for robustness, showing moderate variability and contained medians, which supports their suitability for dynamic environments.

The rolling-window test amplifies the trade-off between flexibility and stability: while highly adaptive models excel in-sample, their predictive reliability deteriorates under temporal shocks, favoring parsimonious and regularized specifications.

Overall, the empirical evidence suggests that the specifications considered provide a good fit to quarter-to-quarter relative changes in BEL. However, the

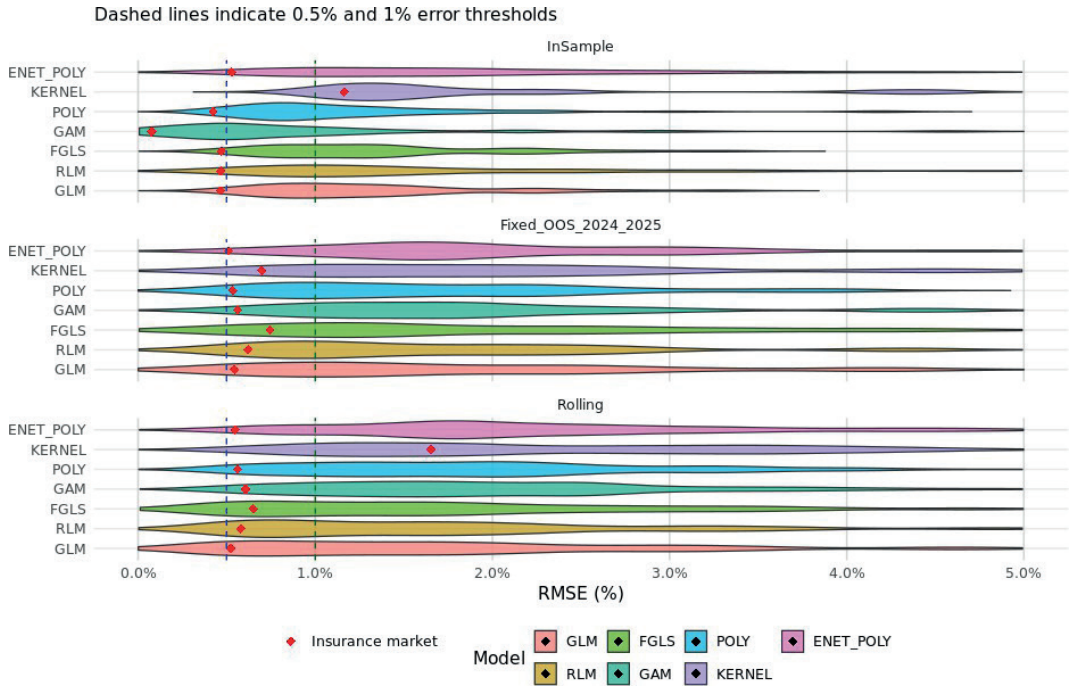
estimated coefficients should be interpreted with caution as regressors embed both price and volume effects, and particularly latter is partly endogenous to BEL dynamics, which can overstate individual parameter estimates. Within these caveats, regression-based proxy approaches appear promising for supervisory and macroprudential oversight applications.

The choice of the preferred specification ultimately depends on the intended use. For broad sensitivity analyses and for stress-testing frameworks where interpretability and stability are essential, a Gaussian GLM—with prior variable selection performed via LASSO—represents a highly reliable and parsimonious benchmark. In cases where, for a given undertaking, the estimated relationships exhibit statistically significant curvature (e.g., nonlinear exposure, convexity, or elasticity effects), the polynomial specification offers additional degrees of freedom and allows the model to incorporate second-order responses to shocks in the explanatory risk factors.

For the insurance market as a whole, the average out-of-sample RMSE is close to 0.5%, even in the most stringent rolling-window evaluation, despite BEL fluctuations ranging from approximately -8.6% to +7.4% over the period examined. These results confirm that the proposed class of models is capable of capturing the essential dynamics of BEL movements under shocks to market and balance-sheet drivers.

Figure 3

RMSE distribution across undertakings by model and evaluation design: in-sample, fixed out-of-sample, and rolling-window out-of-sample



4.4 Marginal Effects and Sensitivity Analysis

To complement the performance evaluation, marginal effects for the insurance market aggregate are computed to quantify local sensitivity of BEL with respect to each explanatory factor. This exercise provides an interpretable summary of the direction and magnitude of the link between changes in asset variables and contemporaneous variations in insurers' liabilities. Importantly, the focus is not on long-term dynamic effects or multi-period pass-throughs, but on instantaneous partial derivatives of the regression.

A repeated LASSO selection replicated many times under random cross-validation splits is used to identify those regressors that consistently enter the best penalized model. This repeated-selection approach mitigates the randomness inherent in single CV splits and isolates factors with robust predictive relevance. Only variables that are selected with sufficiently high frequency are retained for the subsequent estimation of marginal effects. By conditioning each model on this reduced set of regressors, the analysis ensures comparability across estimation techniques while avoiding spurious effects induced by irrelevant or weakly identified variables.

Since many of these models do not yield closed-form gradients, marginal effects are computed through a carefully controlled finite-difference procedure. For each regressor, the estimation sample is perturbed by a very small increment, scaled to be proportional to the empirical variability of that variable. This ensures that the numerical perturbation is economically negligible, avoiding jumps into regions unsupported by the data, while being large enough to exceed machine precision and avoid numerical instability. The model is then re-evaluated at the perturbed dataset, and the discrete difference in the predicted BEL is divided by the size of the perturbation. Averaging this local difference quotient across all observations yields an estimate of the global average partial derivative, which is the natural quantity for interpreting the effects of shocks in a sector-level proxy model. This approach ensures that the marginal effect reflects the structure of the fitted model rather than any particular observation. So, for every X_j is computed

$$ME_j = \frac{1}{n}\sum_{i=1}^{n} \frac{\hat{f}(X_{i,1},\ldots,X_{i,j}+h_j,\ldots,X_{i,p}) - \hat{f}(X_{i,1},\ldots,X_{i,j},\ldots,X_{i,p})}{h_j}. \qquad (22)$$

where $\hat{f}()$ is the model specification (GLM, GAM, Kernel, POLY, etc.), h_j is the infinitesimal increase for variable X_j and n is the number of observations used when computing marginal effects ME. The step h_j is a small fraction of the empirical standard deviation of X_j:

$$h_j = 10^{-3}\,\mathrm{sd}(X_j), \qquad \text{and if } \mathrm{sd}(X_j) = 0 \text{ then } h_j = 10^{-6}.$$

Thus, the predictions are

$$\hat{y}_i^{\text{orig}} = \hat{f}(X_{i,1}, \ldots, X_{i,j}, \ldots, X_{i,p}), \tag{23}$$

$$\hat{y}_i^{\text{pert}} = \hat{f}(X_{i,1}, \ldots, X_{i,j} + h_j, \ldots, X_{i,p}). \tag{24}$$

The local margin effect per observation is then:

$$\Delta_{i,j} = \frac{\hat{y}_i^{\text{pert}} - \hat{y}_i^{\text{orig}}}{h_j}. \tag{25}$$

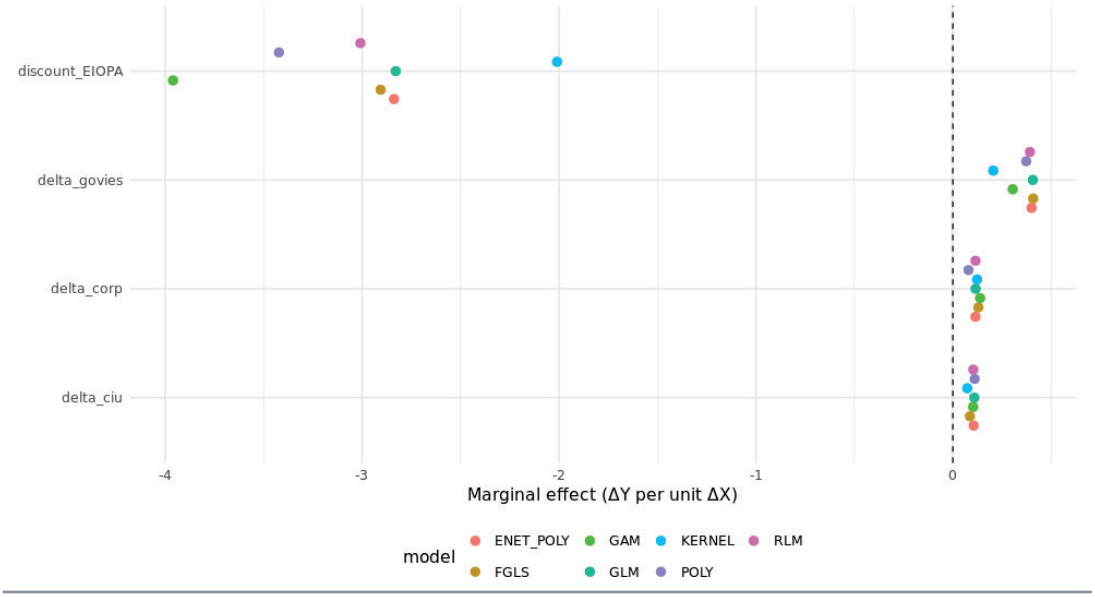
The average across all observations provides a stable, interpretable, global sensitivity index for each predictor and each model.

$$ME_j = \frac{1}{n}\sum_{i=1}^{n} \Delta_{i,j} \approx \frac{\partial \hat{f}(X)}{\partial X_j}. \tag{26}$$

By applying the same perturbation-based derivative approximation across all models, the results become directly comparable. The comparative analysis allows to assess not only how each factor affects BEL but also whether nonlinear structures or regularisation materially change these sensitivities. For supervisors, such information is essential for understanding model uncertainty, validating the stability of the proxy under alternative specifications, and ensuring robustness in the construction of instantaneous shocks. Figure 4 shows the marginal effects of the main variables selected by the LASSO selection at market level for every specification, identified by color.

Figure 4

Marginal effects of the main variables selected by LASSO on the quarterly change in BEL for the market aggregate



The empirical results clearly indicate that the EIOPA discount factor ($r_t(D)$) represents the dominant driver of variations in BEL. The estimated marginal effect is consistently negative across all model specifications, with an average value of approximately -3 and a range between -3.96 and -2.01, accompanied by a standard deviation of 0.598. Both the sign and the magnitude of this coefficient are fully consistent with the underlying valuation logic: an increase in the risk-free rate reduces the present value of future liability cash flows and therefore lowers BEL. At the same time, the relatively wider dispersion of the estimated effect across different model specifications suggests the presence of non-linearities along the discount curve, particularly at longer maturities. These non-linear effects are captured more strongly by flexible model specifications, such as generalized additive models or high-order polynomial regressions, which tend to produce more extreme estimates when compared with simpler linear formulations.

Turning to the asset side of insurers' balance sheets, the results show that the main fixed-income asset classes display positive and robust marginal effects. In general terms, increases in the market value of investments are associated with higher levels of BEL. This relationship can arise from several mechanisms, including declines in interest rates, tightening of credit spreads, or net purchases and portfolio rebalancing. The positive sign is consistent with the institutional features of traditional life insurance business models, particularly those characterized by with-profit arrangements. Under these frameworks, improvements in asset performance or an expansion of the invested asset base translate into higher expected future credited rates for policyholders, thereby increasing the expected liability cash flows and, consequently, the BEL. Within the fixed-income segment, government bonds represent the most important asset-side driver after the discount curve. The marginal effect associated with changes in the market value of government bonds is estimated at approximately +0.356, with a range between +0.205 and +0.408 and a standard deviation of 0.075, indicating a strong and highly robust relationship across model specifications. Increases in the market value of government securities, whether resulting from falling interest rates, spread compression, or net portfolio purchases, are therefore associated with higher BEL. Two complementary mechanisms may explain this result. The first is the already mentioned profit-participation channel, the second relates to portfolio composition and duration effects: for instance, if insurers increase their holdings of longer-duration government bonds in periods of declining interest rates, both the market value of assets and the sensitivity of liabilities to future credited returns may increase simultaneously. Corporate bonds constitute the second most important fixed-income driver. The estimated marginal effect for changes in the market value of corporate bonds is approximately +0.117, with a relatively narrow range between +0.080 and +0.139 and a standard deviation of 0.019. The limited dispersion across models suggests a stable and well-identified relationship. Variations in credit spreads and net allocations to corporate bonds therefore appear to move closely with BEL dynamics, again reflecting the role of asset performance in shaping the expected returns that un-derpin future policyholder participation. A similar effect is observed for CIUs, its estimated marginal effect is approximately +0.099, ranging between +0.074 and +0.111, with a standard

deviation of 0.014. This moderate but highly stable positive relationship indicates that broader market improvements, tend to increase BEL through the same mechanism linking higher expected investment returns to higher future policyholder benefits.

By contrast, the technical flow variables, namely premiums, claims, and expenses, exhibit extremely small estimated effects. Their marginal impacts are approximately -0.007 for premiums, -0.003 for claims, and +0.004 for expenses, with very limited dispersion across model specifications. At the quarterly frequency and at the aggregated sectoral level considered in this study, these effects are economically negligible. Their contribution to the overall variation in BEL is therefore minimal, which justifies their exclusion from the main graphical summaries presented in the analysis. Similarly, equity exposures do not appear to play a material role in explaining sector-level BEL dynamics.

Taken together, the estimated effects display a high degree of internal consistency with the economic and institutional features of traditional life insurance business. It should be noted that the asset-class variables, such as changes in government bonds, corporate bonds, and the CIU indicator, capture both market price movements and portfolio management decisions. Their estimated marginal effects should therefore be interpreted as semi-reduced-form relationships rather than as purely causal effects of interest rates or credit spreads.

An important feature of the results is their robustness across model specifications. The ranking of the main drivers and the sign of their estimated effects remain stable when different classes of models are considered. Dispersion across models is lowest for the asset-class variables, indicating that their effects are relatively stable regardless of the chosen specification. By contrast, the dispersion is larger for the risk free rate factor, reflecting the fact that some models (e.g. GAM, POLY) are better able to capture non-linearities along the interest rate curve.

Finally, note that the aggregation at the sector level may mask significant heterogeneity across individual undertakings, particularly in terms of asset-liability management strategies, profit-sharing rules, and duration mismatches between assets and liabilities.

4.5 Discussion on market-only vs. full specification, loss absorbing capacity and stress tests.

Marginal effects analysis clarifies the hierarchy of economic drivers. Equity exposure plays virtually no role at the sector level, though it becomes relevant for a small subset of firms with material equity books. Quarterly variations in premiums, claims, and expenses display systematically lower marginal impacts relative to asset-class revaluations. This is economically intuitive as quarterly movements in asset positions reflect both market valuation effects and balance-sheet adjustments induced by policyholder behaviour including lapses and premium inflows. The relative importance of explanatory variables therefore mirrors the underlying asset

allocation and the liability structure of the sector. Therefore, technical flows are excluded in the following analysis.

A central implication of the empirical framework concerns its application to the estimation of the loss absorbing capacity of technical provisions (LAC TP), one of the most important features of the Solvency II framework. LAC TP reflects the insurer's ability to absorb part of market losses through the adjustment of policyholder benefits. In with-profit business, contractual benefits consist of a guaranteed component and a discretionary participation element linked to asset performance. When financial markets deteriorate, insurers experience investment losses, but can offset part of the impact by lowering the discretionary component, thereby reducing liabilities and mechanically improving the Solvency Ratio. Precisely because of this feedback mechanism, any proxy model used to estimate BEL must be calibrated in a strictly market-consistent manner.

LAC TP is, by definition, the sensitivity of liabilities to shocks originating from the asset side, consequently, the inclusion of quarterly variations in premiums, claims, expenses, or other technical flows contaminates the elasticity and may distort the estimate of pass-through from market losses to discretionary benefits. In this context, a further complication arises because, in Balance Sheet data, quarterly movements embed not only pure market valuation effects but also active portfolio management and policyholder behavior – notably lapses and net premium inflows. In an instantaneous stress-test scenario, such behavioural adjustments should not be assumed to materialize immediately, and therefore must not influence the estimated BEL. If these behavioural and management components are not filtered out, the empirical elasticity of ΔBEL with respect to $\Delta Assets$ will generally be overstated. This requires moving to the asset-by-asset reporting level, retrieving both market values and quantities for all non-unit-linked and non-index-linked assets, and decomposing the total change of value into a price effect and a quantity effect. By re-estimating the models using the decomposition, the resulting specification can be more faithfully applied to stress test scenarios and can reduce simultaneity distortions. Also, any application must incorporate an explicit supervisory constraint, where the reduction in liabilities cannot exceed the available Future Discretionary Benefits (FDB). This cap is essential to ensure consistency with the contractual structure of policyholder participation and to avoid mechanically producing implausible or non-admissible liability reductions during severe market dislocations.

A further practical challenge emerges when the baseline estimation for some insurers yields statistically insignificant coefficients for key market drivers such as the discount curve, sovereign bonds, corporate bonds, or collective investment undertakings. In the context of a stress test, it would be economically incoherent to impose large shocks to these asset classes while allowing the liability side to remain insensitive simply because baseline regressions indicate low significance. From a supervisory perspective, these core market variables must always enter the stress-test specification, regardless of firm-specific insignificance in baseline data. A rigorous solution consists in adopting a cluster-based estimation strategy. Firms are first grouped into clusters according

to similarity in asset allocation, liability duration, and other structural characteristics. Because differenced quarterly data can be treated time independent, the pooled data within each cluster can be used to estimate a common market-only elasticity to ΔBEL, after removing outliers associated with mergers, portfolio transfers, or other idiosyncratic events. For any insurers whose baseline model does not yield significant coefficients for variables that must be included in the stress test, the corresponding sensitivities are then imputed from the cluster-level estimates. This ensures internal consistency across the market, preserves an economically meaningful transmission mechanism from asset shocks to liability adjustments, and avoids the implausible conclusion that large market shocks could leave certain insurers' BEL unaffected.

Overall, the proposed proxy framework delivers encouraging results, including when backtested against the outcomes of bottom-up european stress testing exercises 2021 and 2024, not reported here for brevity. Although it should be interpreted as an approximation, the approach provides a practical tool for assessing liability sensitivities in situations where granular information is available only on the asset side.

A possible refinement would consist in isolating the pure market component of BEL variations, for instance by removing technical-flow regressors and filtering out volume effects embedded in asset allocation variables. Table 5 reports the results of the Granger Causality test (see Granger 1969) on the aggregate market data. While endogeneity in cross-sectional frameworks is typically addressed via contemporaneous tests (such as the Durbin-Wu-Hausman, see Hausman 1978 and Wu 1973), the Granger test is specifically employed here to detect temporal precedence and feedback loops inherent in raw balance-sheet reporting. A statistically significant feedback loop is observed, specifically for Government Bonds and is rejected the null hypothesis that ΔBEL does not Granger-cause the regressor ($p < 0.05$). This result is critical since sovereign bonds represent the largest share of the portfolio and indicates that past liability movements statistically predict future asset allocation changes, likely due to liquidity management actions (e.g., selling assets to pay surrenders) or strategic rebalancing. This evidence provides the mathematical justification for the structural price-volume decomposition proposed in Section 5, which strips out the lagged behavioral dynamics to isolate the market sensitivity.

Table 5

Granger-causality tests on market-aggregate data: evidence of feedback effects from BEL to selected asset-side variables. The test evaluates the null hypothesis H_0: ΔBEL_{t-1} does not Granger-cause ΔX_t. Rejection of H_0 implies a feedback loop (endogeneity)

Variable (X)	F-Statistic	p-value	Significance
Δ Gov	5.386	0.0266	**
Δ Corp	1.110	0.2997	n.s.
Δ Equity	0.414	0.5244	n.s.
Δ CIU	1.828	0.1855	n.s.

Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, n.s. not significant

5 Decomposing Balance-Sheet Dynamics: Market Sensitivities vs. Volume Effects in the Estimation of BEL Variations and Orthogonalization of Risk Factors

A fundamental insight emerging from the empirical work conducted so far is that the adopted representation of Section 4, while extremely convenient for sector-wide supervisory analysis, is not fully coherent when the objective is to approximate instantaneous stress-test sensitivities.

The reason is intrinsic to the business model of traditional life insurance. Balance-sheet quantities on both sides are jointly determined: premiums, benefit payments, reinvestment flows, coupon receipts, guarantees, and the active management of assets interact continuously with the valuation of BEL. As a result, the quarterly variation of asset holdings – used in the regressions as explanatory variables – already embeds both market movements and policyholder-driven volume adjustments that are themselves influenced by the evolution of BEL. Thus, the empirical regressors are not purely exogenous market factors, but rather a compound of market returns and endogenous quantity effects.

This implies that, in a quarterly Solvency II dataset, a non-negligible share of the explanatory variation arises from volume dynamics that depend (i) on policyholder behaviour (premium inflows, lapses, surrenders, switches), (ii) on internal managerial decisions (rebalancing, tactical allocation changes), and (iii) on contractual features linked to the evolution of BEL itself. Therefore, the regressions estimated in the previous sections – although highly predictive and statistically robust – implicitly conflate price elasticities and volume elasticities, generating models whose coefficients cannot be interpreted as pure market sensitivities.

For sector-level nowcasting or for measurement of historical elasticities this is largely acceptable: volume changes are multiplicative effects that the regression naturally absorbs through the coefficients. However, in a supervisory stress-test framework, where the shock is instantaneous and behavioural responses may be not assumed to materialise, the decomposition between price-driven and quantity-driven components should be tested.

5.1 A Micro-Level Decomposition of Market Value Changes

To isolate genuine market-price effects, the granularity of the Solvency II templates at the asset-by-asset level is exploited. For each undertaking *i*, for

each reporting date *t*, and for each ISIN-level position *j*, the market value (MV) satisfies:

$$MV_{i,t,j} = P_{i,t,j} \cdot Q_{i,t,j} + AI_{i,t,j},$$

where:

- $P_{i,t,j}$ is the clean market price (percentage-of-par for bonds; unit price for equities and CIU);
- $Q_{i,t,j}$ is the quantity (par amount for bonds; number of units for equities and CIU);
- $AI_{i,t,j}$ is the accrued interest component (for bonds).

Given *d* as the absolute change between two quarters, the total change in market value decomposes into:

$$dMV_{i,t,j} \simeq Q_{i,t-1,j} dP_{i,t,j} + P_{i,t-1,j} dQ_{i,t,j} + dAI_{i,t,j}.$$

The decomposition relies on a first-order approximation, ignoring the cross-term $dP_{i,j}dQ_{i,j}$, that will be discussed later on. This formula yields a structural separation between:

1. Price effect

$$dMV_{i,t,j}^{\text{price}} = Q_{i,t-1,j} dP_{i,t,j} + dAI_{i,t,j},$$

capturing movements in market conditions (interest rates, spreads, equity prices, fund NAVs).

2. Quantity effect

$$dMV_{i,t,j}^{\text{quantity}} = P_{i,t-1,j} dQ_{i,t,j},$$

reflecting policyholder behaviour, reinvestment flows, active management, and other endogenous volume adjustments.

This decomposition can be computed thanks to the Solvency II template which provides for each ISIN the clean price, the amount or quantity, the accrued interest, the residual modified duration, the maturity date and the full market value. The quantity-driven component is computed first, by multiplying the change in holdings between *t* – 1 e *t* by a representative clean price for the period, typically the midpoint between the clean prices observed at the two reporting dates. The residual component, obtained as the difference between the total variation in market value and the quantity effect is then attributed to pure price dynamics, including both the change in clean price applied to the prior-period quantity, the evolution of accrued

interest for fixed-income instruments and the cross-term. All elements that are not volume-driven, i.e., all effects due to market movements, yield curve shifts, spread changes, equity repricing, fund NAV changes, and the mechanical accrual of coupon interest – are therefore consistently assigned to the price effect.

Aggregation by Asset Class and Undertaking. After computing the de-composition at ISIN level, the variables used in the regressions are reconstructed by aggregating over asset categories. For each undertaking *i*, the aggregate price and quantity driven absolute variations are:

$$dX_{i,t,k}^{\text{price}} = \sum_{j \in k} dMV_{i,t,j}^{\text{price}}, \qquad dX_{i,t,k}^{\text{quantity}} = \sum_{j \in k} dMV_{i,t,j}^{\text{quantity}},$$

where (k $\in$ Gov, Corp, Equity, CIU).

Finally, quarter-to-quarter relative changes are computed: $\Delta X_{i,t,k}^{\text{price}}, \Delta X_{i,t,k}^{\text{quantity}}$. Thus, instead of one regressor for asset class, two structurally interpretable regressors per class are obtained: one reflecting pure market shocks, and one representing volume dynamics.

Re-estimating BEL Sensitivities: Isolating the Market-Only Component. Once the full decomposition is available, the regression for each firm becomes:

$$\Delta \text{BEL}_i = \sum_k (\beta_{i,k}^{\text{price}} \Delta X_{i,k}^{\text{price}} + \beta_{i,k}^{\text{quantity}} \Delta X_{i,k}^{\text{quantity}}) + \gamma_i \Delta \text{r}(D_i) + \varepsilon_i \tag{27}$$

This specification allows to distinguish the elasticities of BEL to pure market shocks (i.e $\beta_{i,k}^{\text{price}}$), the only coefficients that should contribute to LAC TP, whereas the one related to endogenous balance-sheet volumes ($\beta_{i,k}^{\text{quantity}}$), which reflect behavioural, managerial or seasonal effects and must be switched off under instantaneous stress (if it's not addressed). The models proposed in Section 4, continue to perform very well, especially from the perspective of the insurance market aggregate (see Figure 5). The violin plots illustrate the distribution of RMSE values across undertakings and time windows. Two reference thresholds are shown in the figure, corresponding to 0.5% and 1% of quarterly BEL relative variation. In the majority of cases, the market-level RMSE values lie below the 0.5% threshold, indicating that the models are able to reproduce quarterly variations in BEL with relatively small errors. The general pattern confirms that the decomposition of asset variations into price and quantity components does not materially deteriorate the predictive performance observed in the baseline specification.

From the undertaking perspective, the violin plots reveal some differences in the dispersion of errors across model classes. Most models produce relatively concentrated RMSE distributions, with typical errors centered well below the 1% threshold. In particular, the generalized linear models, feasible generalized least squares, polynomial regressions, and robust linear models display comparatively tighter distributions, indicating greater stability across rolling windows.

Figure 5

Rolling-window RMSE by model after decomposing asset changes into price and quantity components

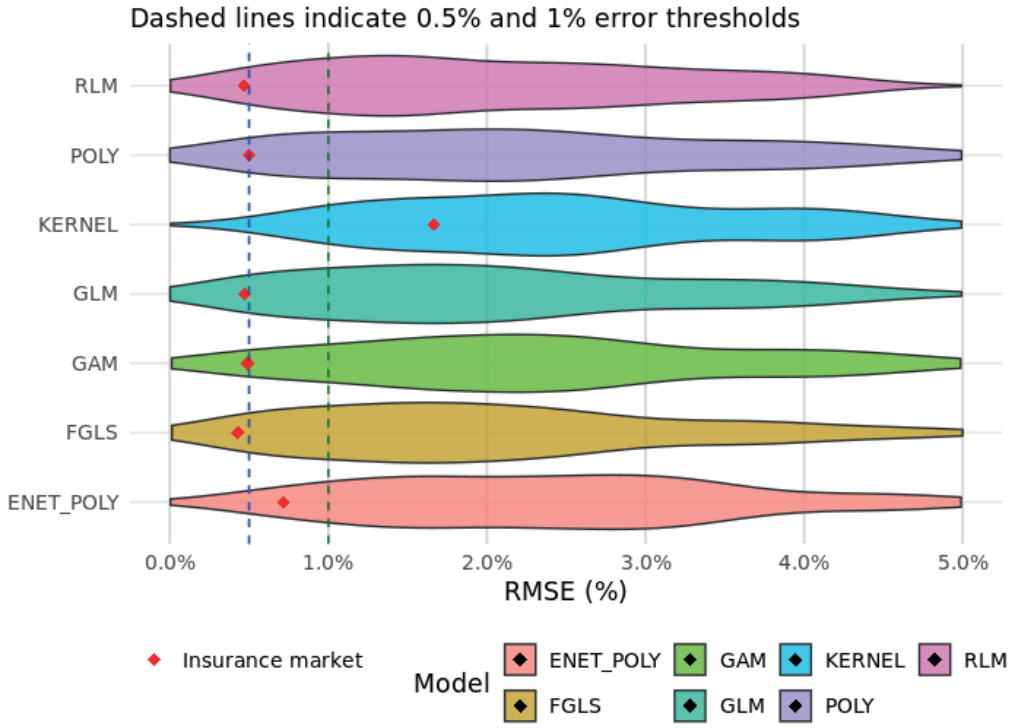


Figure 6 illustrates the main marginal effects of both market and volume at sector level on the BEL relative change. Consistent with the results obtained in the baseline analysis, the discount factor remains the dominant explanatory variable. Its marginal effect is negative and large in magnitude, around -3.5 per unit change in the explanatory variable, with some model specifications producing estimates closer to -4. The dispersion observed across model classes remains non-negligible, which is consistent with the presence of non-linearities along the risk-free curve, particularly at longer maturities where small shifts in interest rates can generate more pronounced valuation effects.

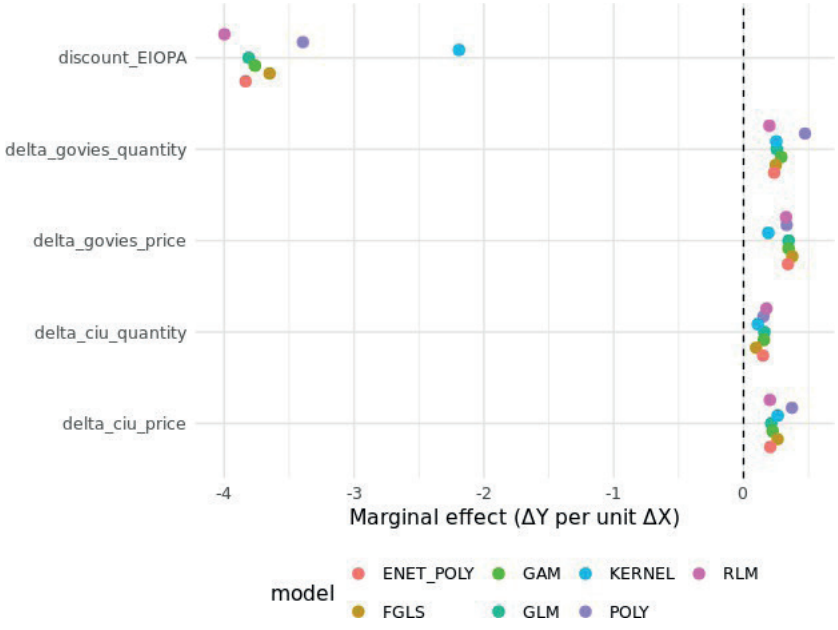
When the government bond exposure is decomposed into price and quantity effects, both channels display a positive relationship with the variation in BEL, although the price component generally appears larger than the quantity component across most models. The quantity effect has marginal effects ranging between approximately +0.25 and +0.5. This result suggests that when insurers expand their holdings of sovereign bonds, or rebalance their portfolios toward this asset class, the level of BEL tends to increase. The price component has marginal effects broadly ranging between +0.33 and +0.45 across models. Mark-to-market gains in sovereign bond portfolios, typically associated with declining interest rates or compression in sovereign spreads, are therefore linked to higher BEL. The economic interpretation again reflects the profit-sharing structure typical of traditional life products.

A similar pattern emerges for CIU, where both the quantity and the price components show positive marginal effects across model specifications, although the magnitude of the price effect again tends to exceed that of the quantity effect. The quantity component is consistently positive, ranging between approximately +0.08 and +0.2. The price component exhibits larger effects, in a range that broadly spans from about +0.1 to +0.45 depending on the model. This suggests that mark-to-market improvements in the value of fund investments also translate into higher liabilities through the same profit-sharing mechanism observed for other asset classes.

Corporate bond exposures tend to be excluded by the LASSO variable selection, once the price-quantity decomposition is introduced. At the aggregated market level, this outcome is economically plausible. The revaluation effects associated with changes in the risk-free term structure are already captured by the discount factor variable, which directly affects the valuation of liabilities. In addition, the dynamics of credit spreads embedded in corporate bond valuations tend to be strongly correlated with those observed for sovereign bonds over the sample period. As a result, the incremental explanatory power of the corporate bond variables becomes limited once the effects of the discount curve and sovereign bond exposures are accounted for. Further analysis of the role of credit risk and corporate bond allocations is therefore deferred to the subsequent sections of the paper (see 5.2). A similar argument applies to equity exposures, which display limited additional explanatory power at the aggregated market level.

Figure 6

Marginal effects of price and quantity components on BEL changes for the market aggregate



Implications for Supervisory Stress Testing. When an instantaneous stress test is performed on BEL, all volume-driven components are explicitly set to zero, because no behavioral adjustments are assumed to materialise at once. Given regressors for each asset class *k* and their price relative change ΔP_k in the scenario *S*, the proxy estimates the raw change in BEL:

$$\Delta BEL_S^{market} = \sum_k \beta_k^{price} \cdot \Delta \mathrm{P}_{k,S} + \gamma \cdot \Delta r_S \tag{28}$$

However, the recognition of the loss-absorbing capacity is capped by the available FDB. The allowable adjustment is therefore defined as:

$$dBEL_S^{final} = \gamma \cdot \Delta r_S + \max\left(\sum_k \beta_k^{price} \cdot \Delta \mathrm{P}_{k,S}\,,\, -FDB_{pre-stress}^{discounted_S}\right) \tag{29}$$

Where *d* represent the absolute variation and β^{price} are the coefficients estimated in Section 5.1 using the decomposition. This formulation ensures that the proxy does not generate artificial capital generation through endogenous volume assumptions.

5.2 The Structural Ambiguity of the Risk-Free Curve

A pervasive challenge in modeling the volatility of BEL arises from the structural dependency of both asset and liability valuations on the risk-free term structure.

Including both asset price changes, ΔGov^{price} and $\Delta Corp^{price}$ and the discount rate change ($\Delta r(D)$) as regressors introduces severe multicollinearity. This phenomenon renders the model identification precarious. While the models may explain the total variance of ΔBEL with high accuracy ($R^2 \approx 0.95$), the attribution of variance to specific drivers becomes unstable.

This structural ambiguity is empirically evidenced at market aggregate level by the Variance Inflation Factors (VIF) reported in Table 6. The VIFs for government bond prices, corporate bond prices, and the discount rate are pathologically high,

Table 5

Variance inflation factors for the market-aggregate specification: evidence of multicollinearity among fixed-income price variables and the discount-rate factor

Regressor	VIF	Interpretation
$\Delta Corp^{price}$	> 15.0	Critical Multicollinearity
$\Delta r(D)$	= 10.0	Critical Multicollinearity
ΔGov^{price}	> 5	Multicollinearity
$\Delta Others$	< 2.0	Acceptable

confirming that these regressors contain overlapping information regarding the interest rate environment.

5.2.1 Orthogonalization of Fixed-Income Price Components

To solve this identification problem and isolate the idiosyncratic risk premia (spreads) from the systematic interest rate risk, a two-stage orthogonalization procedure is implemented.

For each insurance undertaking *i* and for each bond asset class $k \in \{Gov, Corp\}$, the duration of the corresponding portfolio, denoted as $D_{i,t,k}$ is assigned to the corresponding point on the swap curve, $r_t(D_i = D^k_{i,t})$.

The observed price variation $\Delta P_{i,t,k}$ is then decomposed into a systematic component explained by the swap rate and an idiosyncratic residual (spread). The estimation equation is defined as follows:

$$\Delta P_{i,t,k} = \beta_{i,k} \cdot \Delta r_t(D_{i,t,k}) + u_{i,t,k} \tag{30}$$

Then:

- $\beta_{i,k}$ captures the sensitivity of the asset price to the swap rate.
- The fitted value, $\hat{\beta}_{i,k}\Delta r_t = \hat{\Delta P}^{swap}_{i,t,k}$, represents the pure interest rate component of the price change.
- The residual, $\hat{u}_{i,t,k} = \Delta P_{i,t,k} - \hat{\Delta P}^{swap}_{i,t,k}$, represents the spread component.

Crucially, the residual term $\hat{u}_{i,t,k}$ captures all non-swap drivers of price changes. This includes the credit spread volatility (country risk for government bonds, credit risk for corporates), liquidity premia, and the accrual of interest (to the extent it impacts the market value change not explained by the curve shift). By construction, $\hat{u}_{i,t,k}$ is orthogonal to the swap rate movements at the specific duration of the asset.

It should be noted that this specification assumes a first-order linear relationship between price variations and rate movements, neglecting the convexity of fixed-income securities. A potential and more refined extension of the model consists in adopting a polynomial regression that includes a quadratic term proportional to Δr^2, in order to explicitly capture the convexity effect within the orthogonalization process.

5.2.2 The ALM-Consistent Regression Model

Having isolated the spread components, the primary regression model for ΔBEL of equation 27 is reformulated. The objective is to estimate the elasticity of liabilities to distinct, uncorrelated risk factors.

The refined specification is defined as:

$$\begin{aligned}\Delta BEL_i = \gamma_0 \cdot \Delta r(D_i^d) \\ + \beta_1 \cdot \hat{u}_i^{Gov} \\ + \beta_2 \cdot \hat{u}_i^{Corp} \\ + \beta_3 \cdot \Delta P_i^{Equity} + \beta_4 \cdot \Delta P_i^{CIU} \\ + \sum_j \lambda_j \cdot \Delta Q_i^j + \varepsilon_i\end{aligned} \tag{31}$$

Interpretation of Coefficients. The re-parameterization allows for a direct economic interpretation of the coefficients, consistent with Asset-Liability Man-agement (ALM) theory:

1. **The Net Duration Effect** (γ_0): The regressor $\Delta r_t(D_i^d)$ is the sole representative of the interest rate environment. Since the asset spread components (û) have been purged of rate effects, γ_0 captures the net sensitivity of the balance sheet to rates. It can be interpreted as a measure of the duration mismatch. The apex *d* indicates which cash-flow duration the risk-free rate refers to, with *d* = *Liab, Ass, Mis*. In this application the discount rate is evaluated at the maturity corresponding to the liabilities' duration *Liab*, but one can either choose the assets' duration or the duration mismatch, depending on the purpose of the analysis.

2. **Idiosyncratic Spread Effects (β_1, β_2):** These coefficients measure the transmission of credit spread volatility into the BEL. For government bonds, this proxies the impact of sovereign risk. For corporates, it reflects the credit rating and default risk premia.

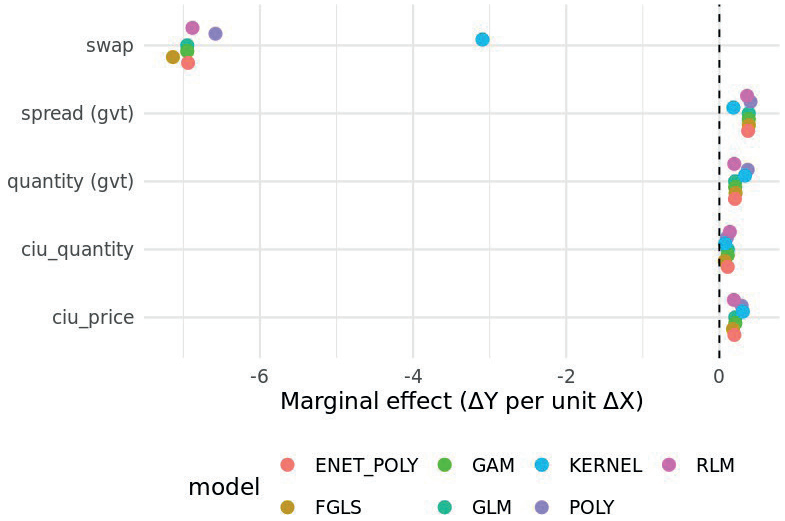
3. **Idiosyncratic Price Effects (β_3, β_4):** These coefficients represent the pure price component variation of equities and CIU NAVs. Note that the price of NAVs could also be decomposed, isolating the swap, spread and equities components underlying the fund, but this analysis is not conducted at this stage because look-through idata are not available.

4. **Volume Effects (λ_j):** The quantity components (ΔQ) capture changes in the magnitude of exposure driven by endogenous factors such as policyholder behavior (lapses, new premiums) or management discretion (portfolio rebalancing), net of market price movements.

Figure 7 presents the new marginal effects of regressors on the market aggregate, after the lasso pre-selection. The dominance of the swap component confirms that interest rate risk remains the primary driver of liability volatility, while the significant coefficients on the spread components highlight the non-negligible impact of sovereign risk on the solvency position.

Figure 7

Marginal effects for the orthogonalized specification: disentangling swap, spread, price, and quantity components in the market-aggregate BEL proxy



The dominant role of the interest-rate environment is confirmed by the marginal effect associated with the change in the swap curve ($\Delta r_t(D)$). Across the different model specifications, the coefficient remains consistently negative and large in magnitude, with an average value of about -6.36 and estimates ranging between -7.14 and -3.09. Compared with the earlier specifications, the absolute magnitude of this effect increases substantially. The spread-driven price component of government bond portfolios remains positive and economically meaningful across all models, with coefficients ranging between approximately 0.18 and 0.41 and an average value of about 0.36. This result indicates that improvements in sovereign bond valuations driven by spread compression are associated with higher BEL. Importantly, isolating the spread component does not mechanically reduce the importance of the price channel relative to the quantity channel; rather, it clarifies its economic interpretation and reduces the contamination from interest-rate effects that were previously embedded in the same variable. The quantity component of government bond exposures is also positive and relatively stable across model specifications, with an average coefficient close to 0.25 and values ranging between about 0.19 and 0.37.

The price component of CIU exposures displays a positive marginal effect across all models, with an average value of about 0.23 and a relatively contained dispersion. The quantity component of CIU holdings exhibits a smaller but still consistently positive effect, with an average coefficient close to 0.10 and very limited variability across model classes. The relatively low dispersion suggests that this effect is structurally stable and reflects a modest scale effect.

Again, once the swap and spread components are separated, corporate bond variables are not selected by the regularized regressions. The interest-rate sensitivity embedded in corporate bond prices is captured by the swap-driven discount factor, while the

residual spread dynamics tend to be strongly correlated with those observed in sovereign bonds over the sample period. As a result, the sovereign spread component effectively absorbs most of the explanatory content associated with credit-market conditions. A similar argument applies to equity exposures, which do not appear to provide additional explanatory power once the main interest-rate and fixed-income channels are explicitly identified in the model. Clearly, these results are different from an undertaking perspective, but are not shown here for brevity.

5.3 Stress Testing Framework and Behavioral Dynamics

Building upon the orthogonalization of risk factors presented, a modular stress testing framework is proposed. This approach distinguishes between instantaneous exogenous market shocks, where the balance sheet is static, and endogenous management actions, where volume adjustments are optimized in response to the post-stress capital and liquidity position (e.g. deleveraging, fire sales).

Exogenous Market Shocks: The Static Balance Sheet Assumption. When computing the impact of market stress scenarios, volume-driven compo-nents are explicitly constrained to zero ($\Delta Q = 0$). This constraint enforces the assumption that no behavioral adjustments or portfolio rebalancing mate-rialize instantaneously. Leveraging the orthogonalized regression specification, the variation in BEL under a market stress scenario *S* is derived by applying exogenous shocks to risk drivers. The estimation equation is defined as:

$$\Delta BEL_S^{price} = \hat{\gamma}_0 \cdot \Delta r_S(D^{Liab}) + \sum_f \hat{\beta}_f^{spread} \cdot \Delta P_{f,S}^{spread} + \sum_l \hat{\beta}_l^{price} \cdot \Delta P_{l,S} \tag{32}$$

Where:

- Δr_S represents the shock to the risk-free curve in scenario S. It quantifies the simultaneous revaluation of the discounting curve and the interest-rate-sensitive assets.
- $\Delta P_{f,S}^{spread}$ represents the relative change in prices due to spread component of asset class *f* (e.g., Gov, Corp) in scenario S.
- $\hat{\beta}_f^{spread}$ are the coefficients associated with the orthogonalized spread regressors.
- $\Delta P_{l,S}$ represents the relative change in class l (e.g. Equity, CIU) prices.
- $\hat{\beta}_l^{price}$ are the coefficients associated with the price of Collective Investment Undertakings and Equity.

The specification of the spread shock vectors allows for varying degrees of granularity. In cases of high portfolio concentration – such as the "home bias", aggregated spread factor may suffice due to the high correlation structure between sovereign and corporate bonds of the same country. Conversely, for diversified

portfolios, the vectors *f, l* can be expanded to capture specific shocks by country or credit rating bucket or corporate sectors.

Endogenous Volume Adjustments: Management Actions. Following the instantaneous market shock, the model allows for second-round effects. Here, market variables are held constant at their post-stress levels, and the model solves for optimal volume adjustments (ΔQ). This simulates management actions aimed at restoring solvency or liquidity metrics. The variation due to management actions is modeled as:

$$\Delta BEL_S^{action} = \sum_j \hat{\lambda}_j \cdot \Delta Q_{j,S}^* \tag{33}$$

Where ΔQ represents the vector of volume changes derived from an optimization function, such as:

$$\Delta Q^* = \arg\max_Q \left(\text{Solvency Ratio}\right)$$

or

$$\Delta Q^* = \arg\max_Q \left(\text{Liquidity needs}\right)$$

This separation allows for a clean attribution of capital consumption between pure market movements and the mitigating (or exacerbating) effects of management decisions.

Finally, the recognition of the liability reduction due to market shocks is not unbounded. The loss absorbing capacity of TP is structurally limited by the amount of discretionary benefits available to absorb losses. To enforce this boundary condition, the final proxy for the change in BEL under stress is defined in equation (29). Where $FDB_{pre-stress}$ represents the stock of FDB prior to the shock. This floor ensures that the model does not generate artificial capital creation by reducing guaranteed technical provisions below their contractual minimums.

5.3.1 Limitations and Approximations

While the proposed linear approximation provides a robust and computationally efficient proxy for liability dynamics, several structural limitations remain, primarily driven by the lack of "look-through" data and non-linear option behaviors.

Collective Investment Undertakings (CIUs). The pricing mechanism of CIUs is modeled as a direct function of their Net Asset Value (NAV). However, the underlying sensitivity of a CIU to swap rates, spreads, or equity shocks is often opaque without full look-through. Consequently, shocks are applied directly to the fund price index rather than its constituents. A proposed extension to this framework involves a sub-proxy categorization, segmenting

CIUs into homogeneous clusters (e.g., Bond Funds, Equity Funds, Hedge Funds) to estimate category-specific *s* betas ($\hat{\beta}_s^{CIU}$), thereby reducing basis risk.

Financial Guarantees and Option Moneyness. The linear regression model approximates the change in BEL effectively when the market moves within a moderate range. However, it does not explicitly capture the convexity associated with minimum return guarantees (financial options) embedded in traditional life policies. As guarantees move deep in-the-money, the sensitivity of the BEL changes non-linearly, a phenomenon essentially representing the decomposition of the liability into a host contract plus a put/call option. Future iterations of this model could focus on the polynomial expansion terms or regime-switching regression to capture the time value of options and guarantees more accurately.

6 Further extensions and conclusions

6.1 Moving Toward Risk-Driver-Based Parametrisation

The decomposition described in section 5 is still expressed in terms of price changes, which are observable but not yet mapped to primitive risk drivers, just in subsection 5.2 has been conducted an assessment to evaluate prior risk drivers, but always with proxies that start from the actual flows.

A natural progression from the price-volume decomposition is the mapping of price variations onto primitive risk drivers. While the separation of ΔX^{price} removes endogenous volume effects, it remains a "black box" regarding the source of the market shock, or, on the other hand, the sensitivity has so far been computed only from observed asset side price movements, but the relation between liabilities and risk drivers is unknown. To fully enable stress-testing capabilities – specifically for assessing sensitivities to exogenous shifts in the risk-free curve, sovereign spreads, or credit ratings – a Risk-Driver Based Factorization is introduced. This framework reconstructs the theoretical price variation of the asset portfolio by aggregating ISIN-level sensitivities. For a given undertaking *i* at time *t*, let J_i be the set of all investment lines. The clean price $P_{t,j}$ of a generic asset $j \in J_i$ is defined as a differentiable function of a vector of risk factors Ω_t. Using a first-order Taylor expansion, the percentage price change for fixed-income assets is modeled as:

$$\frac{\Delta P_{t,j}}{P_{t-1,j}} \approx -D_j \cdot \Delta y_{t,j}(\tau_j) \tag{34}$$

where $-D_{t-1,j}$ is the modified duration and $\Delta y_{t,j}(\tau_j)$ is the variation in the yield-to-maturity specific to asset *j* with residual maturity τ_j. The objective is to decompose the yield variation into its structural components based on the asset class *k*. Crucially, instead of modelling yield variations at the level of individual issuers, countries, or rating categories – which would introduce significant multicollinearity

and compromise model stability – yield movements are aggregated into duration-adjusted risk factors, capturing the portfolio's effective sensitivity to each underlying driver.

6.1.1 Risk-Driver Specification

Risk-Free Rate (Swap Curve):

The risk-free component is represented by movements in the swap curves rep-resentative of the insurers' portfolios, weighting fixed-income exposures by geographic area *a* (namely *a* = EU, US, JP, UK,...):

$$\Phi_{i,t}^{swap}(D_i) = \sum_{a \in Area} \omega_{i,a,t-1} \cdot r_{a,t}(D_{i,t-1}), \tag{35}$$

Sovereign Bonds:

For sovereign debt, the yield variation is split into the risk-free rate change (Δr) and the country-specific spread change (Δs^{Gov}). Rather than modeling country-specific spreads as separate regressors, a portfolio-representative sovereign spread factor adjusted for duration is constructed:

$$\Phi_{i,t}^{Gov-spread}(D_i) = \sum_{c \in Gov_i} \omega_{i,c,t-1} \cdot s_{i,c,t}^{Gov}(D_{i,t-1}), \tag{36}$$

where $\omega_{i,c,t-1}$ is the portfolio weight of government bonds of country *c* for undertaking *i*, and $s_{i,c,t-1}^{Gov}(\mathrm{D}_{i,t-1})$ denotes the sovereign spread of country *c* at the duration point $\mathrm{D}_{i,t-1}$ of the government bond portfolio of undertaking *i*. This construction collapses country, maturity, and exposure information into a single duration-weighted sovereign spread factor, capturing the effective sensitivity of the undertaking's sovereign portfolio to spread shocks, while avoiding redundant regressors.

Corporate Bonds:

For corporate bonds, the same approach of sovereign bonds could be used. Yield changes are decomposed into the risk-free rate and a credit spread component, indexed by rating bucket. The effective corporate spread exposure is defined as:

$$\Phi_{i,t}^{Corp-spread}(D_i) = \sum_{b \in Corp_i} \omega_{i,b,t-1} \cdot s_{i,b,t}^{Corp}(D_{i,t-1}), \tag{37}$$

where *b* denotes the credit rating bucket of the corporate bond. By aggregating across ratings using duration-adjusted weights, the model captures the overall sensitivity of the corporate bond portfolio to credit risk without proliferating highly correlated regressors.

Collective Investment Undertakings and Equities:

For non-fixed income assets or funds where a full look-through is unavailable, a mapping function $\Psi(j) \rightarrow \mathbf{w}_j$ that associates the asset to a vector of proxy indices I *is* used. The price change is approximated as:

$$\frac{\Delta P_{j,t}}{P_{j,t-1}} \approx \sum_m \lambda_{j,m} \frac{\Delta I_{m,t}}{I_{m,t-1}} \tag{38}$$

where λ represents the weight of the index and *m* the number of indices. For mixed funds, this allows for the "transposition" of the shock: a bond fund is treated as a proxy of spread/swap variations, while an equity fund responds to equity indices. Thus:

$$\Phi_{i,t}^{Eq} = \sum_m \lambda_{i,m,t} \cdot \frac{\Delta I_{i,m,t}}{I_{i,m,t-1}} \tag{39}$$

6.1.2 Aggregation and BEL Regression

The objective is to regress the relative variation of BEL not on the aggregate asset value change, but on the theoretical *P&L* attributed to each risk driver. Finally, for the undertaking *i*, the specification for BEL sensitivity becomes:

$$\Delta BEL_i = \beta_{swap}\Delta\Phi_i^{Swap} + \beta_{gov}\Delta\Phi_i^{Gov-Spread} + \beta_{corp}\Delta\Phi_i^{Corp-Spread} + \beta_{eq}\Delta\Phi_i^{Eq} + \varepsilon_i \tag{39}$$

This formulation allows for the precise injection of instantaneous stress scenarios by inputting a theoretical shock vector into the Φ terms, the model predicts the consequent reaction of BEL in a fully consistent market-value framework.

The volume component can instead be modelled directly as a function of policyholder behaviour, premium dynamics, lapses, surrenders, and internal asset-allocation policies. This will make the regression framework fully risk-driver based, enabling scenario extrapolation and improving interpretability within supervisory macroprudential toolkit.

6.2 Conclusions

This paper develops and evaluates a framework for approximating quarterly relative movements in BEL using regression-based proxy models calibrated on supervisory Solvency II data, and could be used in top-down stress test exercises. By combining a broad spectrum of parametric, semi-parametric, and non-parametric specifications with rigorous variable selection and extensive out-of-sample validation, it is shown that relatively parsimonious statistical relationships can successfully capture the short-term sensitivity of liabilities to observed balance-sheet and market-consistent drivers. The empirical results, obtained across a heterogeneous set of 36 Italian life insurers, plus the market aggregate, over nine

years, indicate that even simple linear or polynomial structures – with appropriate regularisation or robustification – deliver high explanatory power and stable predictive performance.

At the same time, the analysis highlights several important methodological challenges and natural limitations.

First, all proposed proxies have been tested on the Italian life insurance market. The use of these proxies in other geographical contexts should be preceded by an assessment of local contractual features, which can be inferred through an analysis of historical quarterly variations. Also, when applied to large, regulatory-sized shocks – often far outside historical ranges – these models necessarily operate out-of-domain, where linearity, smoothness, or monotonicity assumptions may no longer hold. This limitation applies not only to flexible models such as GAMs or kernel regressions, but also to seemingly simple linear or polynomial specifications. Even the latter implicitly assume that liability responses behave smoothly, whereas in reality option-like features in traditional life products may generate state-dependent nonlinearities, such as guarantees abruptly moving in-the-money when interest rates fall below contractual floors. These structural features cannot be easily captured by linear-local approximations and may lead to under- or over-estimation of liability movements under severe scenarios. This issue may remain material even if the models perform well, on average, on historical stress-test data.

Second area of attention concerns the statistical limitations imposed by the sample size. The analysis relies on a quarterly time series of 37 observations, a physiological constraint linked to the availability of Solvency II reporting data. Within such a restricted time frame, training highly flexible models, such as elastic nets or generalized additive models, rapidly depletes the available degrees of freedom, increasing the risk of in-sample overfitting. Furthermore, the application of LASSO regularization for variable pre-selection can suffer from parametric instability when estimated via cross-validation over a small number of folds. Although the selection procedure was rigorously iterated through repeated sampling to ensure the robustness of the chosen regressors.

Third, the quarterly Solvency II data inherently mix price effects and volume effects, including policyholder behaviour, premium dynamics, lapses, asset reinvestment, and managerial rebalancing. Without explicit decomposition, these dynamics induce endogeneity between $\Delta Assets$ and ΔBEL, as confirmed by the Granger causality evidence. The market-only decomposition proposed in the paper mitigates this concern by isolating pure price movements; however, even after separation, the framework remains silent on scenario-dependent management actions, which are likely to be material under a stress scenario. In particular, rebalancing behaviour, whether mechanical (e.g., duration matching) or discretionary, can significantly alter the asset-liability interaction in ways that cannot be inferred from historical data. The absence of explicit rebalancing equations implies that

the proxies approximate only the static, observed transmission mechanism, but not the dynamic decision rules that firms may adopt under stress. Moreover, the current orthogonalization of asset-side shocks relies on linear approximations with respect to movements in the risk-free curve. Future developments of this framework could integrate the convexity of the bond portfolio, for instance, by including second-order expansion terms.

Fourth, the proxy models do not embed a structural mapping from market drivers to asset-level price changes. While this section outlines a possible pathway for a full risk-driver factorisation, future research could strengthen external validity by integrating duration- and rating-based price sensitivities directly into the regression framework, thereby allowing stress scenarios to be applied in a more consistent and interpretable manner.

More broadly, the results underscore the need for careful model governance when using proxies in a regulatory environment. Statistical fit alone does not guarantee economic plausibility under stress; conversely, economically coherent restrictions – such as capping liability reductions at the available FDB – may be necessary to ensure the regulatory admissibility of the outputs.

The development of cluster-level elasticities for firms with weak firm-specific signals represents an additional avenue for ensuring supervisory consistency while preserving the underlying heterogeneity of business models.

The proxies developed here offer an interpretable approximation of BEL sensitivities for supervisory macroprudential purposes; however, their limitations must be recognised when operating in the presence of strong nonlinearities and management reactions. Future work should focus on integrating risk-driver-based price decompositions and modelling management actions more explicitly. These extensions would further enhance the robustness and regulatory usefulness of proxy-based stress-testing top-down frameworks within the Solvency II environment.

References

Bai, Jushan, Sung Hoon Choi, and Yuan Liao (2020). *Feasible Generalized Least Squares for Panel Data with Cross-sectional and Serial Correlations*. arXiv: 1910.09004 [econ.EM]. url: https://arxiv.org/abs/1910.09004.

Barigou, Karim, Valeria Bignozzi, and Andreas Tsanakas (2022). "Insurance valuation: A two-step generalised regression approach". In: *ASTIN Bulletin: The Journal of the IAA* 52.1, pp. 211-245.

Bauer, Daniel, Andreas Reuss, and Daniela Singer (2012). "On the Calculation of the Solvency Capital Requirement Based on Nested Simulations". In: *ASTIN Bulletin: The Journal of the IAA* 42.2, pp. 453-499. doi: 10.2143/AST.42.2.2182255.

Castellani, Gilberto et al. (2018). "An investigation of machine learning approaches in the Solvency II valuation framework". In: *Available at SSRN 3303296*.

EIOPA (2019a). *Discussion Paper on Methodological Principles of Insurance Stress Testing*. url: https://www.eiopa.europa.eu. – (2019b). *Methodological Principles of Insurance Stress Testing*. url: https ://www.eiopa.europa.eu.

Eisele, Karl-Theodor and Philippe Artzner (2011). "Multiperiod insurance supervision: top-down models". In: *European Actuarial Journal* 1.1, pp. 107-130.

European Parliament and European Council (2009). *Directive 2009/138/EC on the taking-up and pursuit of the business of insurance and reinsurance (Solvency II)*. Articles 112-127, Directive.

Feng, Runhuan and Hans W. Volkmer (2012). "Analytical calculation of risk measures for variable annuity guaranteed benefits". In: *Insurance: Mathematics and Economics* 51.3, pp. 636-648. doi: 10.1016/j.insmatheco.20 12.09.007.

Gergonne, J.D (1815). "The application of the method of least squares to the interpolation of sequences". In: *Historia Mathematica* 1.4, pp. 439-447. issn: 0315-0860. doi: https://doi.org/10.1016/0315-0860(74)90034-2. url: https://www.sciencedirect.com/science/article/pii/0315086074900342.

Granger, Clive WJ (1969). "Investigating causal relations by econometric models and cross-spectral methods". In: *Econometrica: journal of the Econometric Society*, pp. 424-438.

Hartmann, S. (2015). "Verallgemeinerte lineare Modelle im Kontext des Least Squares Monte Carlo Verfahrens". In.

Hastie, T. and R. Tibshirani (1986). "Generalized additive models". In: *Statistical Science* 1.3, pp. 297-318. – (1990). *Generalized Additive Models*. London, UK: Chapman & Hall.

Hausman, Jerry A (1978). "Specification tests in econometrics". In: *Econometrica: Journal of the econometric society*, pp. 1251-1271.

Hendrych, Radek and Tomáš Cipra (2017). "Econometric model of non-life technical provisions: the Czech insurance market case study". In: *European Ac-tuarial Journal* 7.1, pp. 257-276.

Hoerl, Arthur E. and Robert W. Kennard (1970). "Ridge Regression: Biased Estimation for Nonorthogonal Problems". In: *Technometrics* 12.1, pp. 55-67. issn: 00401706. url: http://www.jstor.org/stable/1267351 (visited on 03/23/2026).

Hurvich, C.M., J. S. Simonoff, and C.-L. Tsai (1998). "Smoothing parameter selection in nonparametric regression using an improved Akaike information criterion". In: *Journal of the Royal Statistical Society, Series B* 60.2, pp. 271-293.

IAIS(2021). *Application Paper on Macroprudential Supervision*. url: https://www.iais.org/uploads/2022/01/210830-Application-Paper-on-Mac roprudential-Supervision.pdf. – (2024). *Insurance Core Principles and Common Framework for the Super-vision of Internationally Active Insurance Groups*. url: https://www.iais.org/uploads/2025/06/IAIS-ICPs-and-ComFrame-December-2024.pdf.

Kopczyk, D. (2018). *Proxy modeling in life insurance companies with the use of machine learning algorithms*. Working Paper. https://ssrn.com/abstrac t=3396481.

Krah, A.-S. (2015). "Suitable information criteria and regression methods for the polynomial fitting process in the LSMC model". MA thesis. Germany: Julius-Maximilians-Universität Würzburg.

Krah, A.-S., Z. Nikolić, and R. Korn (2018). "A least-squares Monte Carlo framework in proxy modeling of life insurance companies". In: *Risks* 6.2, p. 62.

Krah, Anne-Sophie, Zoran Nikolić, and Ralf Korn (2020). "Machine learning in least-squares Monte Carlo proxy modeling of life insurance companies". In: *Risks* 8.1, p. 21.

Nadaraya, E. A. (1964). "On estimating regression". In: *Theory of Probability and Its Applications* 9.1, pp. 141-142.

Nelder, J.A. and R. W. M. Wedderburn (1972). "Generalized linear models". In: *Journal of the Royal Statistical Society, Series A* 135.3, pp. 370-384.

Nikolić, Z., C. Jonen, and C. Zhu (2017). "Robust regression technique in LSMC proxy modeling". In: *Der Aktuar* 1, pp. 8-16.

R Core Team (2018). *stats: R statistical functions*. R package version 3.2.0, R Foundation for Statistical Computing, Vienna, Austria. http://www.R-pro ject.org.

Schelthoff, T. (2019). "Machine learning methods as alternatives to the least squares Monte Carlo model for calculating the solvency capital requirement of life and health insurance companies". MA thesis. Germany: Universität zu Köln.

Schoenenwald, J.J. (2019). "Modelli proxy per la determinazione dei requisiti di capitale secondo Solvency II". MA thesis. Italy: Università degli Studi di Trieste.

Tibshirani, Robert (1996). "Regression Shrinkage and Selection via the Lasso". In: *Journal of the Royal Statistical Society. Series B (Methodological)* 58.1, pp. 267-288. issn: 00359246. url: http://www.jstor.org/stable/2346178 (visited on 03/23/2026).

Watson, G.S. (1964). "Smooth regression analysis". In: *Sankhýa: The Indian Journal of Statistics, Series A* 26.4, pp. 359–372.

Wedderburn, R.W.M. (1974). "Quasi-Likelihood Functions, Generalized Linear Models, and the Gauss Newton Method." In: Biometrika, 61, 439-447.

Wu, De-Min (1973). "Alternative tests of independence between stochastic regressors and disturbances". In: *Econometrica: journal of the Econometric Society*, pp. 733-750.

Zou, Hui and Trevor Hastie (2005). "Regularization and variable selection via the elastic net". In: *Journal of the Royal Statistical Society Series B: Statistical Methodology* 67.2, pp. 301-320.

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