Chapter 19.

PERFORMANCE EVALUATION OF OPTIMAL INVESTMENT STRATEGIES IN INSURANCE

The insurance industry is pivotal in the global economy, serving as a fundamental pillar of financial stability. Central to insurance companies' operations is managing their investment portfolios, which sustains their financial viability and significantly influences their capacity to fulfill their contractual obligations and achieve long-term growth objectives. As such, evaluating and optimizing investment strategies within the insurance sector is paramount in ensuring the industry's resilience and competitiveness amidst evolving market dynamics and regulatory landscapes.

Over the years, insurance companies have grappled with the complexities of investment decision-making, striving to balance risk and return while navigating economic, financial and regulatory challenges. Adopting optimal investment strategies has become imperative for insurers seeking to enhance their profitability, liquidity and solvency positions in an increasingly competitive marketplace. Against this backdrop, this chapter examines the performance of various investment strategies to offer actionable insights and practical recommendations for industry stakeholders.

We evaluate and compare optimal investment strategies for European insurance companies, drawing upon quantitative analysis and empirical evidence to assess their efficacy and suitability under different market conditions. By scrutinizing the performance of diverse investment approaches that insurance companies could employ, this research sheds light on the critical determinants of success and failure in portfolio management within the insurance industry.

Specifically, we implement a passive benchmark and an optimal investment portfolio strategy and cross them with two volatility timing strategies based on realized variance and downside semi-variance. Our test assets consist of European government bonds, corporate bonds and equity, representing the typical content of investment portfolios of European insurance firms. We compare all approaches based on four performance metrics: spanning regression alpha, Sharpe ratio, Sortino ratio and Omega ratio. Our results highlight the benefits of both optimization and volatility management and have important practical implications for investment portfolio allocation.

The remainder of this chapter is organized as follows. Section 1 provides a literature review. Section 2 presents the methodology. Section 3 describes the data. Empirical results are given in Section 4. Section 5 concludes.

1. RELATED LITERATURE

Optimal investment strategies in insurance have been studied extensively in the literature. Earlier research established a simple but compelling argument for why insurers should optimize. Schlarbaum (1974) shows that common stock portfolios of property-liability insurance companies experienced significantly lower returns than random portfolios of equivalent risk between 1958 and 1967. Haugen and Kroncke (1970) present a technique for optimizing the portfolios of claims and investments and the degree of leverage in the capital structure of a stock insurance company.

Insurance companies can and do adopt various investment approaches. For example, Wang (2007) shows that an insurer should invest a fixed amount in each risky asset, maximizing the exponential utility of its reserve at a future time. Annaert et al. (2009) argue for an active investment approach. They show that portfolio insurance strategies outperform buy-and-hold strategies, including stop-loss, synthetic put, and constant proportion. According to Azcue and Muler (2010), an insurance company's optimal investment and dividend payment strategy maximizes cumulative expected discounted dividend payouts until bankruptcy, with the optimal value function being the smallest viscosity solution. A model proposed by Mao and Wen (2013) optimizes insurance pricing and investment strategies for insurers with multi-dimensional time-varying correlations, proving that an equally weighted investment portfolio can be optimal under certain conditions. Peng and Wang (2016) provide evidence that the optimal investment and risk control strategies for an insurer with inside information on the financial market can be derived using forward integral approach and enlargement of filtration techniques.

Another strand of literature investigates the critical factors in optimizing investment strategies for insurance companies. Liu and Yang (2004) show that optimal investment strategies can minimize insurance companies' probability of ruin, with risk-free assets playing a risk-free role and stock volatility affecting investment decisions. Bo and Wang (2017) state that the optimal investment and risk control strategy for an insurer under stochastic factors is to maximize the expected power utility of terminal wealth by allocating wealth across riskless bonds and risky assets. Koch-Medina et al. (2019) find that optimal investment strategies for value-maximizing insurance firms depend on the tradeoff between investment risk and the owner's option to default, with regulatory and financial environment changes affecting these strategies. The copula effect can significantly impact the investment portfolio of an insurance company, as it allows for non-linear dependencies between correlated stochastic variables (Pranevičius and Sutiene, 2008). Mazzoccoli and Naldi (2019) show that optimal investment decisions in mixed insurance/investment cyber risk management can reduce overall security expenses, with insurance premiums being the dominant component. Božović (2023a) studies the challenges in forming insurers' optimal portfolios in crises and identifies increased risk and uncertainty, data availability and reliability, possible domino effects, limited investment universe and regulatory constraints as the most important ones.

Researchers have also been studying the performance evaluation framework for investment strategies. Plantinga and van der Meer (1995) argue that performance measurement for liability-driven investors, such as insurance companies and pension funds, should be based on a combination of asset and liability approaches to avoid misleading results. Plantinga and Huijgen (2001) present an attribution framework for evaluating the investment performance of insurance companies, balancing shareholder value and policyholder value while reducing agency costs. Bertrand and Prigent (2011) analyze the performance of the two main portfolio insurance methods, the Option Based Portfolio Insurance (OBPI) and the Constant Proportion Portfolio Insurance (CPPI), using downside risk measures. They introduce two measures that take account of the entire return distribution and show that the CPPI method performs better than the OBPI. Tone et al. (2019) develop a dynamic two-stage network data envelopment analysis model and demonstrate that it effectively evaluates insurance company performance by considering investment assets as a carry-over variable. Braun and Schreiber (2020) show that an asset-liability Sharpe ratio is a more suitable performance measure for liability-driven investors like life insurance companies, as it is theoretically motivated, easy to estimate and incentive-compatible.

2. METHODOLOGY

2.1. Portfolio allocation

Consider an investment universe of n assets (or asset classes) with a return vector $\mathbf{r}_t$ at time t. Let $\mathbf{w}$ be an n-dimensional vector of portfolio weights. Then, the portfolio return is simply

$$r_{P,t} = \mathbf{w}'\mathbf{r}_t, \quad (1)$$

where the prime symbol denotes the transpose of a vector. Keeping the weight vector $\mathbf{w}$ fixed over time results in a passive strategy, which maintains a constant proportion of wealth allocated across different assets or asset classes within the investment universe.

We will compare this strategy with the (ex-ante) optimal allocation that involves solving the following problem:

$$\min_{\mathbf{w}_t} \operatorname{var}_t(\mathbf{w}_t'\mathbf{r}_{t+1}), \quad (2)$$

subject to the constraints

$$\begin{aligned} \mathbb{E}_t(\mathbf{w}_t'\mathbf{r}_{t+1}) &\geq \mu_P, \\ \mathbf{w}_t &> 0, \end{aligned} \quad (3)$$

for every month t, where $\mathbb{E}_t$ and var_t represent the conditional expectation and variance, while μ_P is a scalar constant. In other words, in any given month, we seek to minimize portfolio risk, captured by the conditional variance of the portfolio return, while achieving at least some minimal portfolio expected return μ_P. The second constraint in Equation (3) prevents short selling, which is realistic for a typical insurance portfolio. Note that this optimization problem differs from the classical mean-variance optimization, where only the first constraint appears. Without the second inequality in Equation (3), the optimization problem is static and has a simple closed-form solution (see, for example, Božović, 2023a).

Another actively managed alternative follows from a recent strand of literature (Moreira and Muir, 2017; Cederburg et al., 2020; Wang and Yan, 2021). It involves simply scaling of the original exposures inversely by some risk metric. We form this managed strategy by changing the risk exposure to the original (passive or optimized) portfolio using the following scaling rule each month:

$$r_{P,t+1}^{\sigma} = \frac{c_t}{\hat{\sigma}_t^2} r_{P,t+1}, \quad (4)$$

where the scaling factor varies reciprocally to the original portfolio's conditional variance proxy $\hat{\sigma}_t^2$, allowing us to exploit the persistence in conditional volatility. Intuitively, if risk decreases in month t, we will increase our risk exposure by moving funds from cash to riskier assets for the next month $t+1$, and vice-versa.

The scaling coefficient c_t is calibrated such that the managed portfolio maintains the same sample variance as the original one. We burn in the first $\tau = 36$ monthly observations to allow for sufficient observations for calculating the sample variance. We use *daily* return data and an expanding window for the volatility scaling and calibration. We adopt two common approaches and scale the returns in Equation (4) with the realized variance, as in Moreira and Muir (2017), and the realized downside semi-variance, as in Wang and Yan (2021). The latter is aimed at timing the downside risk of the portfolio. Other approaches have also been used, including scaling with higher-order moments or option-implied volatility (see Božović, 2023b). We will not include them here for expositional brevity.

2.2. Performance evaluation

We apply several metrics to evaluate the performance of the managed portfolios compared to the unmanaged alternative. We will compare the two volatility timing strategies to the passive one. Then, we will apply volatility timing to the mean-variance constrained-optimum portfolio.

Our first performance metric is the spanning regression alpha. We follow Moreira and Muir (2017) and run the following time-series regression on monthly data:

$$r^{\sigma}_{P,t} = \alpha + \beta\, r_{P,t} + \varepsilon_t. \quad (5)$$

A significant and positive intercept α in the regression implies that the managed strategy outperforms the unmanaged one.

The second metric is the difference in Sharpe ratios between the managed and the unmanaged portfolio:

$$\Delta = SR^{\sigma} - SR. \quad (6)$$

The statistical significance of this difference can be assessed using the test of Wright et al. (2014). The test statistic Δ is asymptotically distributed as χ^2_1 under the reasonable assumption that Sharpe ratios are stationary and ergodic.

The third metric is a difference in Sortino ratios between the managed and the unmanaged portfolio:

$$\Delta_{(-)} = SR^{\sigma}_{(-)} - SR_{(-)}. \tag{7}$$

The statistical significance of this difference can be assessed using the block-bootstrap procedure of Ledoit and Wolf (2008).

Finally, we adapt the Omega measure of Bertrand and Prigent (2011) and introduce the following metrics:

$$\Omega = \frac{\mathbb{E}\left[\left(r_{P,t} - r_{f,t}\right)^{+}\right]}{\mathbb{E}\left[\left(r_{f,t} - r_{P,t}\right)^{+}\right]}, \tag{8}$$

where the plus symbol denotes the positive part of a function. Omega represents the ratio of expected gains and losses below the threshold, which is set to be equal to the risk-free rate. We calculate this metric separately for the managed and the unmanaged portfolios and compare their numerical values. Since no statistical tests exist to determine the significance of their difference, our comparison will serve illustrative purposes only.

3. DATA

Our test assets consist of European government bonds, corporate bonds and equity. For simplicity, we use market indices as proxies for each asset class. We use the iBoxx EUR Sovereigns Index for government bonds, representing a broad investment-grade fixed-income market index for EUR-denominated sovereign bonds. Corporate bonds are represented via the analogous iBoxx EUR Corporates Index. Both iBoxx indices are provided by IHS Markit.[553] To capture the return on European equities, we use the STOXX Europe 600 index. This index tracks the return of the 600 largest listed companies out of 17 European countries. Besides countries in the Eurozone, it includes stocks from the United Kingdom, Switzerland, and Scandinavian countries. Due to its broad market exposure, it is often considered the European equivalent of the U.S.-focused S&P 500 index.[554]

[553] IHS Markit Ltd. is an information services provider, now part of S&P Global since 2022.

[554] The iBoxx and STOXX indices are standard benchmarks used by mutual funds and ETFs that invest in Europe.

All index data are available from LSEG Eikon. They represent Euro-denominated index levels between January 4, 2005, and April 18, 2024. We use daily frequencies for constructing mean-variance optimization and volatility timing strategies and monthly frequencies for active portfolio formation. The descriptive statistics for the monthly data are shown in Table 1. We use the yield on Euro-denominated 1-year AAA bonds available from the European Central Bank database as the risk-free proxy.[555]

For passive strategy, we construct a typical investment portfolio of a European insurer. We follow the approach similar to Božović (2023a) and use the Asset Exposure Data from EIOPA Insurance Statistics.[556] The Asset overview (EEA) data for 2023 Q3 reveal that around 87.8% of 8.5 trillion Euros of investments were allocated to government bonds, corporate bonds, equity and collective investment undertakings (primarily mutual funds). The remaining 12.2% covers assets such as cash, bank deposits, loans, structured products, collateralized securities and real estate. For simplicity, we will assume that a passive investment portfolio is split only between the three major asset classes and cash proportionally to their total asset exposure. This approach results in the following benchmark asset allocation:

- government bonds 33.5%
- corporate bonds 31.5%
- equity 28.2%
- cash and cash equivalents 6.8%.

The cumulative return of the passive benchmark is displayed in Figure 1.

[555] https://data.ecb.europa.eu/data/datasets/YC/

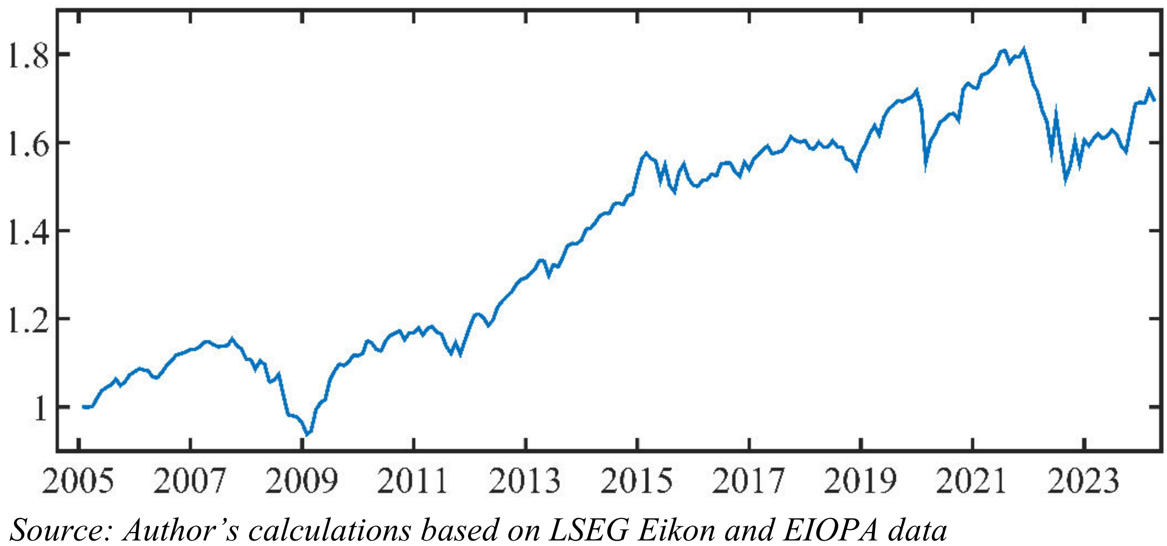
[556] https://www.eiopa.europa.eu/tools-and-data/insurance-statistics_en

Table 1. Characteristics of the dominant asset classes for a typical investment portfolio of a European insurer. The columns represent the average monthly excess return (in percent), the standard deviations of monthly excess return (in percent) and the Sharpe ratio. The data corresponds to the period between February 2005 and April 2024. The benchmark portfolio represents a passive investment portfolio of the three major asset classes and cash based on their average relative proportions in European insurers' assets.

Portfolio	Average return	Standard deviation	Sharpe ratio
Government bonds	0.21	1.41	0.35
Corporate bonds	0.22	1.32	0.39
Equities	0.38	4.20	0.26
Benchmark	0.25	1.65	0.37

Source: Author's calculations based on LSEG Eikon, EIOPA and ECB data

Figure 1. Cumulative return of the passive benchmark investment portfolio for a typical European insurer. The portfolio balances a fixed proportion of assets invested between European government bonds (33.5%), European corporate bonds (31.5%), European equity (28.2%) and cash (6.8%) each month. The line tracks the value of 1 Euro invested in the benchmark from the beginning of the observation period (February 2005) until the end of the sample (April 2024).



Source: Author's calculations based on LSEG Eikon and EIOPA data

4. RESULTS

Table 2 shows the results of spanning regressions. We run the regressions given by Equation (5) for each asset class (government bonds, corporate bonds and equities) separately and then combine them with cash into portfolios. The portfolios are formed with fixed weights (the benchmark asset allocation described in Section 3), and the weights are obtained through a constrained mean-variance optimization, given by Equations (2) and (3). The managed strategies are based on the realized variance (RV, panel A) and realized downside semi-variance (downside RV, panel B).

In the single-asset case, the regression alphas are positive and significant at a 5% level only for corporate bonds with RV-managed strategy. Other asset classes individually do not produce significant alphas, i.e., there are no gains in volatility timing on the asset class level. The same applies to passive allocation: the fixed-weights portfolio yields insignificant alphas. However, the optimal portfolio shows promising profit potential in both managed strategies. The spanning regression alphas are significant at a 5% level, with values of 120 basis points for the RV-managed strategy and 83 basis points for the downside RV-managed strategy. The R^2s are the highest, and the root mean square errors (RMSE) are the lowest among all combinations. Thus, we should expect the most considerable improvement in the Sharpe, Sortino and Omega ratios for the optimal portfolio (cf. Tables 3–5).

Table 3 compares the annualized Sharpe ratios of the managed returns with those of the original ones for the three asset classes and two portfolios constructed by combining these classes with a cash position. The first row of the table contains the Sharpe ratios for the unmanaged asset classes and portfolios, ranging between 0.21 and 0.41. The lower panels show the Sharpe ratio differences (Δ) between the managed and the original returns, defined by Equation (6). The statistical significance of the differences in Sharpe ratios is measured by Wright et al. (2014) test statistics, reported in the brackets. The only consistent statistically significant improvement occurs for the optimal portfolios, where the Sharpe ratio increases by 0.36 for the RV-managed strategy and 0.43 for the downside RV-managed strategy on top of the original 0.40.

*Table 2. Spanning regressions for the three asset classes and two portfolios constructed by combining these classes with a cash position. This table shows results from univariate spanning regressions, given by Equation (5). The portfolios are formed with fixed weights (the benchmark portfolio), and the weights obtained through a constrained mean-variance optimization, given by Equations (2) and (3). The managed strategies are based on the realized variance (RV, panel A) and realized downside semi-variance (downside RV, panel B). The sample period is between 2008-02 and 2024-04. We report the regression alphas (in annualized percentages), the R^2 and the root mean square error (RMSE). Numbers in parentheses are the Huber-White heteroskedasticity-consistent standard errors. The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.*

				Portfolio	
	Gov't bonds	Corporate bonds	Equities	Fixed weights	Optimal weights
Panel A: RV-managed strategy					
Alpha (α)	0.43	1.42**	0.86	0.90	1.20**
	(0.47)	(0.66)	(1.74)	(0.61)	(0.51)
R^2	0.34	0.48	0.41	0.48	0.49
RMSE	15.03	14.10	43.46	12.52	11.75
Panel B: Downside RV-managed strategy					
Alpha (α)	0.37	1.13	0.86	0.73	0.83**
	(0.44)	(0.59)	(1.71)	(0.54)	(0.40)
R^2	0.30	0.47	0.35	0.37	0.49
RMSE	15.64	11.73	45.08	13.78	8.91

Source: Author's calculations based on LSEG Eikon, EIOPA and ECB data

Table 4 shows the analogous comparison of the Sortino ratios, emphasizing the tradeoff between return and downside risk. To assess the statistical significance of the difference $\Delta_{(-)}$, we apply the Ledoit and Wolf (2008) procedure with bootstrap standard errors on 1000 simulations. The improvement brought by the volatility-managed strategies is now highly significant for the government and corporate bonds. For government bonds, the increase is relatively high numerically (1.20 and 1.31), which could be tied to a significant drop in the European sovereign class performance during 2022–2024. Similarly to the Sharpe ratios, the Sortino ratios exhibit a highly significant improvement for optimal portfolios, increasing by 0.63 for the RV-managed strategy and 0.93 for the downside RV-managed strategy above the original 0.46.

We can observe a similar pattern for Omega ratios, shown in Table 5. The most notable improvement is again achieved for the optimal portfolios, where Omega increases from the original 1.06 to 1.58 for the RV-managed strategy and 1.78 for the downside RV-managed strategy. The original Omega ratio of 1.06 for the optimal portfolio is slightly higher than the corresponding value for individual asset classes and the passive benchmark, which range from 0.91 to 1.00. However, genuine improvement occurs when we combine optimization with volatility management. This approach brings an essential reduction in downside risk, allowing investors to benefit from the volatility upside. Naturally, it is more pronounced for the downside RV-managed strategy, making average positive excess returns about 78% higher than the average negative excess returns.

*Table 3. Sharpe ratios for the three asset classes and two portfolios constructed by combining these classes with a cash position. This table compares the annualized Sharpe ratios of the managed factor returns with those of the original ones. The portfolios are formed with fixed weights (the benchmark portfolio), and the weights obtained through a constrained mean-variance optimization, given by Equations (2) and (3). The managed strategies are based on the realized variance (RV, panel A) and realized downside semi-variance (downside RV, panel B). The sample period is between 2008-02 and 2024-04. The lower part of the table reports the Sharpe ratio differences given by Equation (6), while the numbers in brackets are the test statistics of Wright et al. (2014). The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.*

				Portfolio	
	Gov't bonds	Corporate bonds	Equities	Fixed weights	Optimal weights
Original Sharpe	0.32	0.41	0.21	0.34	0.40
Panel A: RV-managed strategy					
Difference (Δ)	0.33*	0.21	–0.10	0.08	0.36*
	[3.12]	[0.88]	[0.21]	[0.15]	[3.83]
Panel B: Downside RV-managed strategy					
Difference (Δ)	0.30	0.33*	–0.10	0.13	0.43**
	[2.69]	[2.72]	[0.18]	[0.37]	[5.79]

Source: Author's calculations based on LSEG Eikon, EIOPA and ECB data

*Table 4. Sortino ratios for the three asset classes and two portfolios constructed by combining these classes with a cash position. This table compares the annualized Sortino ratios of the managed factor returns with those of the original ones. The portfolios are formed with fixed weights (the benchmark portfolio), and the weights obtained through a constrained mean-variance optimization, given by Equations (2) and (3). The managed strategies are based on the realized variance (RV, panel A) and realized downside semi-variance (downside RV, panel B). The sample period is between 2008-02 and 2024-04. The lower part of the table reports the Sortino ratio differences given by Equation (7), while the numbers in brackets are the test statistics of Ledoit and Wolf (2008). The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.*

				Portfolio	
	Gov't bonds	Corporate bonds	Equities	Fixed weights	Optimal weights
Original Sortino	0.48	0.48	0.29	0.45	0.46
Panel A: RV-managed strategy					
Difference ($\Delta_{(-)}$)	1.20**	0.20**	–0.16	0.13	0.63***
	[2.28]	[1.81]	[0.57]	[0.01]	[2.52]
Panel B: Downside RV-managed strategy					
Difference ($\Delta_{(-)}$)	1.31**	0.52**	–0.17	0.28	0.93**
	[2.08]	[2.04]	[0.55]	[0.33]	[1.81]

Source: Author's calculations based on LSEG Eikon, EIOPA and ECB data

The findings from Tables 2–5 can be visualized by plotting cumulative returns for each strategy, with and without optimization. Figure 2 plots the cumulative nominal returns to the RV-managed and downside RV-managed portfolios compared to a buy-and-hold benchmark from April 2008 to April 2024 without optimization. We track a dollar invested in each of the three strategies at the beginning of the observation period. RV- and downside RV-based strategies provide similar gains to the buy-and-hold approach, consistent with the insignificant differences in spanning regression alphas and the three ratios between the original passive strategy and fixed-weight managed strategies. However, the managed portfolios behave more smoothly in recessions, while the original buy-and-hold strategy exhibits notable dips in the last quarter of 2008 and the first quarter of 2020.

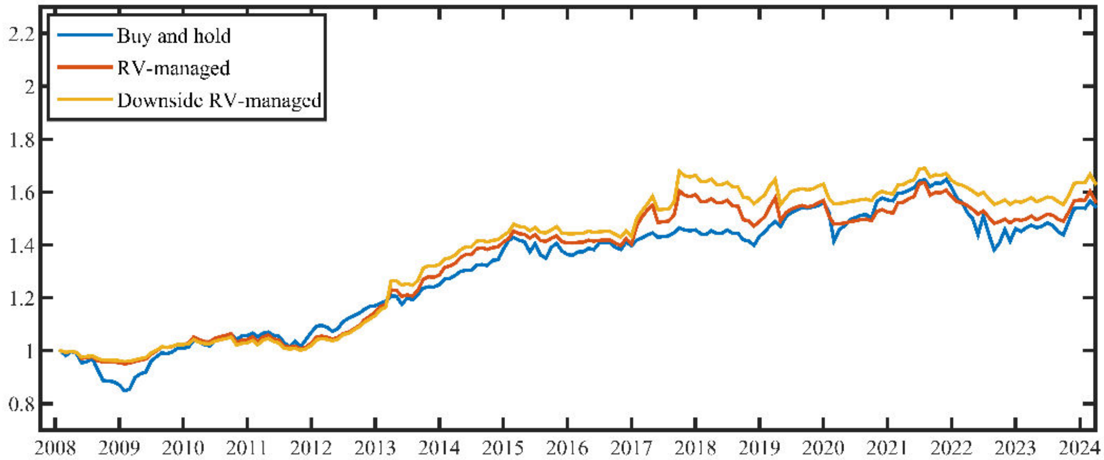
Figure 3 clearly illustrates the benefits of the constrained optimization given by Equations (2) and (3). It compares the managed and unmanaged portfolios. Here, the highly significant spanning regression alpha of 120 basis points for the RV-managed strategy results in its outperformance over the competing approaches. Over the observation period, the investment portfolio's value doubles for the RV-based portfolio.

Table 5. Omega ratios for the three asset classes and two portfolios constructed by combining these classes with a cash position. This table compares the Omega ratios, given by Equation (8), for the managed factor returns with those of the original ones. The portfolios are formed with fixed weights (the benchmark portfolio), and the weights obtained through a constrained mean-variance optimization, given by Equations (2) and (3). The managed strategies are based on the realized variance (RV, panel A) and realized downside semi-variance (downside RV, panel B). The sample period is between 2008-02 and 2024-04.

				Portfolio	
	Gov't bonds	Corporate bonds	Equities	Fixed weights	Optimal weights
Original Omega (Ω)	0.91	1.00	0.91	0.91	1.06
Panel A: RV-managed strategy					
Managed Omega (Ω)	1.48	1.38	0.86	0.99	1.58
Panel B: Downside RV-managed strategy					
Managed Omega (Ω)	1.53	1.50	0.86	1.09	1.78

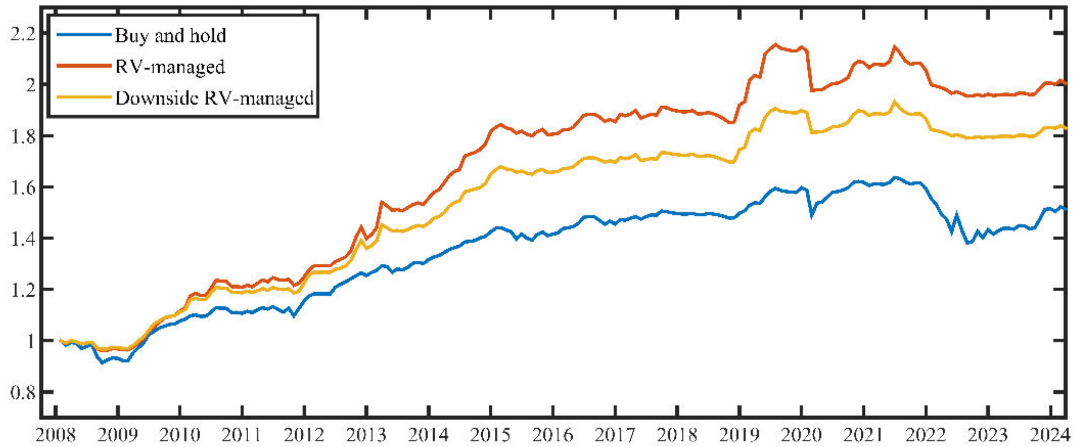
Source: Author's calculations based on LSEG Eikon, EIOPA and ECB data

Figure 2. Cumulative returns of the unmanaged and managed investment portfolios for a typical European insurer. The unmanaged portfolio is a simple buy-and-hold strategy, i.e., the passive benchmark that balances a fixed proportion of assets invested in European government bonds, corporate bonds, equity and cash each month. The managed strategies apply volatility timing of the same portfolio based on the realized variance (RV) and realized downside semi-variance (Downside RV). The lines track the value of 1 Euro invested in each portfolio between April 2008 and April 2024.



Source: Author's calculations based on LSEG Eikon and EIOPA data

Figure 3. Cumulative returns of the optimal investment portfolios for a typical European insurer with and without volatility timing. The buy-and-hold portfolio weights are obtained through a constrained mean-variance optimization, given by Equations (2) and (3). The managed strategies apply volatility timing of the same portfolio based on the realized variance (RV) and realized downside semi-variance (Downside RV). The lines track the value of 1 Euro invested in each portfolio between April 2008 and April 2024.



Source: Author's calculations based on LSEG Eikon and EIOPA data

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In this chapter, we compared the performance of benchmark and optimal portfolios for a typical European insurer whose investment universe consists of sovereign bonds, corporate bonds and equity. The passive benchmark balances a fixed proportion of assets invested in these three asset classes and cash each month. The asset classes are proxied by monthly observations of representative market indices between February 2005 and April 2024. The optimal portfolios involve a constrained mean-variance optimization with short-selling constraints.

We combined the passive buy-and-hold strategies using the fixed-weight and the optimal portfolios with volatility timing strategies based on realized variance and downside semi-variance. We evaluate the performance of unmanaged and managed strategies by spanning regression alpha, Sharpe ratio, Sortino ratio, and Omega ratio. While little could be gained from volatility management on an individual asset-class level, we find notable benefits on a portfolio level. The strategy combining optimal portfolios and volatility timing produces spanning regression alphas between 83 and 120 basis points. The improvements in Sharpe, Sortino and Omega ratios are also significant.

Our results may help us understand the drivers of investment performance and their implications for insurers' financial health and strategic decision-making. They also indicate hidden potential for improving the performance of European insurance companies' investment strategies.

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