Inzinerine Ekonomika-Engineering Economics, 2025, 36(1), 96–112

Sustaining in Uncertain Time: Investigating Pension Fund Performance during Market Stress

Ausrine Lakstutiene[1], Kristina Sutiene[1], Audrius Kabasinskas[1], Aidas Malakauskas[1], Milos Kopa[1, 2]

[1]*Kaunas University of Technology*
K. Donelaicio st. 73, LT-44029, Kaunas, Lithuania
E-mail. ausrine.lakstutiene@ktu.lt; kristina.sutiene@ktu.lt; audrius.kabasinskas@ktu.lt; aidas.malakauskas@ktu.lt; kopa@karlin.mff.cuni.cz

[2]*Charles University*
Ovocny trh 5, Prague 1, 116 36, Czech Republic
E-mail. kopa@karlin.mff.cuni.cz

https://doi.org/10.5755/j01.ee.36.1.36796

The academic discourse on stress in the global economy and financial markets has ignited discussions regarding regulatory oversight of pension fund management and investment strategies. This study investigates how pension funds (PF) respond to short-term and long-term risks, as well as their recovery periods following market shocks. To address these inquiries, we classify financial market stress, considering both short-term and long-term risks. Utilizing the change point detection technique and Bayesian average (Zhao et al., 2019), we analyse shifts in the dynamics of PF values managed by SEB and Swedbank from 2004 to 2023. The research explores not only timings and the number of change points but also their likelihood over time. Drawdowns, recovery rates, and timing ratios are particularly insightful for assessing PF performance during crises and market disturbances. These findings contribute to the understanding of PF behaviour in various market conditions and underscore the significance of adaptive investment strategies in navigating financial uncertainties.

Keywords: *Pension Funds; Market Stress; Short –Term Risk; Long-Term Risk; Change Point Detection.*

Introduction

Pension funds (PFs), in their capacity as institutional investors, oversee financial assets held for future retirement, thereby assuming a pivotal role in future income assurance (Autenne *et al.* 2021; Kopa *et al.* 2022). Given the long-term of their liabilities, PFs must ensure a long-term horizon for their investments in infrastructure and other assets (Bank of England, 2014). With rapidly growing assets under management, PFs have the potential to either stabilise or amplify swings in financial markets and wider economy (Duijm & Bisschop, 2015). An increase of assets managed by PFs calls for a better understanding of their investment strategies and performance (González *et al.* 2020). Given the vital role private pension systems play in financial markets, the effective regulation and supervision of pension funds is paramount. Regulating and supervising pension funds is complicated due to the necessity of guaranteeing their stability and sustainability over a prolonged timeframe. There is a growing emphasis within pension regulations on governance and risk management matters, designed to pinpoint potential critical risks faced by individual pension funds, evaluate the efficacy of risk management strategies employed by these funds, and gauge their financial resilience against diverse macroeconomic shocks (OECD, 2011). Shocks in world economy like the global financial crisis in 2008, European debt crisis in 2010, Covid-19 pandemic, stock market crash in 2020, Russo-Ukrainian war in 2022, sparks scientific debates and questions about how and to what extent regulators and supervisors should influence pension fund management and their investment strategies. These discussions aim to ascertain how regulators and supervisors can influence pension fund activities and ensure profitability and stability over both short and long terms. Most recent regulatory shift is targeted at a more effective PF control, which would allow for identifying uncertainties, focusing on the most problematic areas, analysing the environment, timely detection and assessment of warning signals (Angulo *et al.*, 2018; Lakstutiene *et al*., 2024). According to Duijm and Bisschop (2015), theoretical studies show that during financial stress, pension funds should act as shock absorbers as their long-term investment horizon should allow them to endure short-term price movements, but in practice PFs may act differently. There is not enough research to provide a definitive answer how pension funds respond to various market shocks and how quickly pension fund performance recovers. Following the global financial crisis, most OECD countries embarked on pension system reforms between 2009 and 2013. These reforms allowed the participants an opportunity to select their preferred investment strategies. However, changes in both pension systems and regulatory incentives exhibit variability across different countries. (Kastelein & Romp, 2020). Since the establishment of thethree pillar Lithuanian pension system in 2004, frequent reforms have created distrust amongst its participants. With participation in the second pillar being quasi-mandatory, over 90 % of the eligible labour force opted to join the pension scheme. By 2019, pension accumulation companies began providing pension funds with varying risk levels, determined by the proportion of investments allocated to stocks, ranging from 0 % (conservative) to 100 % (risky) (Bank of Lithuania, 2018). Research conducted in Lithuania (Lieksnis, 2010; Strumskis & Balkevicius, 2016; Medaiskis & Gudaitis, 2017; Medaiskis *et al.*, 2018; Kabasinskas *et al.*, 2020) has indicated that a significant portion of pension fund participants made suboptimal choices regarding their pension fund selection based on investment strategy and risk fundamentals. In response to the identified concerns and with the objective of safeguarding the interests of pension fund participants and their investments, regulatory measures mandated that all pension funds transition to life cycle pension funds starting from 2019 (Bank of Lithuania, 2018). External shocks encourage scientific discussions about the suitable role of regulators and supervisors in influencing pension fund investment strategies and performance results. Therefore, the equilibrium between regulatory intervention and granting professional pension fund managers the authority to make short-term decisions is a crucial consideration. Evaluating the performance and profitability of pension funds influenced by both short-term and long-term risks becomes imperative.

Exploring how PFs, specifically life-cycle funds, respond to both short-term and long-term risks, as well as their recovery times following market shocks, motivates significant considerations. By evaluating the response of pension funds to various market stresses, it was found (Lakstutiene *et al*., 2024) that pension funds generally react in advance to already identified market events, however, it becomes challenging to determine their behaviour when multiple market stresses occur simultaneously. For that reason, research should focus on specific events during periods of market stress. Moreover, participants' expectations regarding life-cycle funds' outcomes are of paramount importance. Therefore, our article aims to address these questions by initially categorizing financial market stress, which includes both short-term and long-term risks. Employing the change point detection technique and by utilizing the Bayesian average (Zhao *et al.*, 2019), we seek to ascertain the shifts in the dynamics of PF values managed by SEB and Swedbank during the period from 2004 to 2023. The study encompasses not only the timings and number of change points but, more importantly, their likelihood over any given time. To assess pension fund performance during market stress, there were chosen indicators that, while interrelated, measure different aspects of pension fund behaviour, drawing on those used by other researchers. Subsequently, we evaluate performance ratios and analyse various measures such as Mean return, Average Recovery, Appraisal ratio, Expected Shortfall, Information Ratio, Timing Ratio, Total (market) risk, and Upside Potential. Each of these measures are different aspects of pension funds performance. Assessing the performance of PFs during a crisis provides crucial insights into their capacity for risk management, flexibility, and overall competence in generating returns amidst challenging market conditions. Drawdowns, recovery, and timing ratios are particularly valuable for evaluating PF performance during times of crises and market disturbances.

The following sections are covered in the paper: literature review, research methodology, results and finding, conclusions and discussion of the key points.

Literature Review

PF risks encompass factors such as longevity, domestic economic performance, and wage growth. PFs seek investment returns to mitigate the risk posed by these factors on contribution rates and benefits paid (Basak & Schapiro, 2001; Menni *et al*., 2018; Hue *et al.*, 2019). The PF investment horizon can span 5, 10, 20 years, or even longer, encompassing the entire economic cycle (Liu *et al*., 2021). Changes in the economic cycle significantly influence the investment returns and performance of pension funds, as numerous market shocks occur over extended periods. The characteristics of long-term returns hold particular importance for investors seeking distant rewards. However, it is essential to note, as highlighted by Fama et al. (2017), that there are fewer observations and less knowledge available regarding the distribution of long-term returns. Evaluating fund performance requires the consideration of return horizons, as a fund's relative performance can vary significantly over different time spans, thereby influencing investor decision-making (Bessembinder *et al.*, 2022). Given the medium-term and long-term nature of pension investments and their sensitivity to economic cycles, it becomes essential to align investment strategies with prevailing economic trends and manage risks effectively in PFs. To achieve this, employing suitable indicators for long-term risk and performance is crucial (Liu *et al*., 2021; Mantilla-Garcia *et al.*, 2024). As emphasized by Hue et al. (2019), global and local economic, structural, regulatory, political, and social changes can swiftly reshape the risk environment, often leading to medium to long-term consequences. The significance of investment horizons is further emphasized by the evidence highlighting the importance of both short-term and long-term PF strategies (Lan *et al.*, 2015). However, PF managers commonly encounter challenges in adapting their portfolios to market conditions (Badea *et al*., 2019). Research reveals a number of issues and problems related to PF performance and returns, which are driven by changes in financial markets, PF investment strategies and institutional factors. The PFs must ensure their portfolio stability against poor financial market performance to ensure compliance with current regulatory constraints and maintain sufficient wealth to meet future regulatory requirements (Kabasinskas *et al.*, 2020). To achieve this, PFs must hold more risk-free assets and fewer risky assets, thus limiting their ability to benefit from favour rable financial market performance (Shi & Werker, 2012). It has been noted that there are growing concerns about PFs adopting short-term investment practices (Hue *et al*., 2019; Bank of England, 2014). This trend includes reduced holdings due to a decreased risk appetite, as well as pro-cyclical investment that exacerbates market volatility. Together, these factors pose threats to the stability of retirement incomes. This perspective is further supported by van Bilsen et al. (2020), Mantilla-Garcia et al. (2024), and Nijman and van Soest (2019), who argue that pension and investment risks are not adequately managed within Defined Contribution funds. The strategies employed by target date funds, which utilize short-term government bonds instead of duration-matching long-term bond portfolios, result in substantial levels of retirement income risk. This situation leaves pension benefits highly uncertain even toward the end of the accumulation period (Mantilla-Garcia *et al.,* 2024). Shi and Werker (2012) explored the economic outcomes arising from a mismatch in planning horizons between institutional investors committed to long-term investment strategies and regulators enforcing short-term prudential standards and practices repeatedly. As noted by Shi and Werker (2012), the misalignment of horizons is prevalent in many developed financial markets and significantly affects pension funds. According to Pastor and Stambaugh (2012), uncertainty regarding anticipated monthly returns can greatly influence the uncertainty surrounding long-term payoffs. Similarly, Fama et al. (2017) suggest that imprecision in estimating expected returns has a substantial impact on the dispersion of possible payoffs from a 20-year investment. Furthermore, the investors can enhance their assessments of distributions of distant payoffs by incorporating uncertainty about expected returns into simulations. Bessembinder et al. (2022) emphasized that investors should not solely focus on short-term arithmetic returns but instead consider compound returns over relevant periods. Their research revealed a decline in the percentage of funds outperforming market benchmarks as the return horizon extends. Lun et al. (2015) revealed that both the overall holdings and transactions of long-horizon funds provide valuable insights into future long-term stock performance. Stocks predominantly held by long-term funds outperform those favoured by short-term funds by approximately 3% annually over the subsequent five years. Similar results were obtained by Hue et al. (2019), indicating that with an increasing time horizon, the long-term trend tends to reach a point beyond which the effects of short-term trading noise become far less relevant.

PFs have a more complex objective function than regular investment funds as they are not only tasked with maximizing returns given a certain risk profile but also must account for the term structure of future payouts (Gonzalez *et al*., 2020). Martellini et al. (2020) and Hue et al. (2019) examined PF strategies to ensure retirees have sufficient income in retirement while also aiming for potential growth. Martellini et al. (2020) noted the dilemma faced by individuals preparing for retirement: they can opt for security but sacrifice flexibility with annuities, or they can choose flexibility but compromise security with investment products like balanced funds or target date funds. This dilemma is further highlighted by Mantilla-Garcia et al. (2024) and Hue et al. (2019), who asserted that current Defined Contribution pension plans often rely on short-term metrics that do not align with the retirement income goals of beneficiaries. Conventional accrual regulations in pay-as-you-go Defined Benefit systems often result in a weak connection between pledged retirement benefits and contributed funds. As a consequence, this leads to liabilities that typically cannot be definitively financed (Mantilla-Garcia et al., 2024). The discrepancy between the timeframes of Defined Contribution funds' bond holdings and the timelines of pension cash flows is termed the "duration puzzle in life-cycle investment" (van Bilsen *et al*., 2020; Mantilla-Garcia *et al*., 2024), which holds particular significance for life-cycle funds. Investing in bonds near retirement within life-cycle funds, especially during stock market downturns, carries the additional risk of underinvestment, as demonstrated by Hue et al. (2019). Following the June 2016 Brexit referendum, equity yields began to decrease, leading to correspondingly higher capital values of perceived liabilities. However, actual investment returns failed to keep pace, resulting in significantly higher assessed shortfalls. Consequently, investors became even less willing to continue the pension scheme (Hue *et al.,* 2019; Breinlich *et al.,* 2018).

To react to changing market conditions, manage investment risks, optimize asset allocation, or evaluate the performance of investment strategy, the change point detection technique could be leveraged. Typically, this approach divides a time series into segments, by identifying sudden shifts in the underlying parameters that generate sequential data (Gupta *et al*., 2024). Such task is often formalized as a mathematical model that includes optimization problem of some multivariate cost function or criteria (Xiao *et al.,* 2019). More advanced methods combine many competing models, which is known as ensemble modeling. Within this class of models, Bayesian paradigm has advantage to embrace all potential models, estimate their likelihood of being true, and combine them into one model (Zhao *et al.,* 2019). For financial application, Habibi (2021) demonstrated how the change point detection based on Bayesian setting performs under various scenarios of different time series by demonstrating its flexibility to adapt to different dynamics. Yümlü et al. (2015) employed Bayesian Inference techniques and Sequential Monte Carlo (SMC) approach to estimate the unknown number of changepoints in GARCH and EGARCH volatility models. Long-term dynamic asset allocation problem is particularly relevant for PF managers. For example, Chen et al. (2014) examined the dynamic asset allocation problem under conditions where investors encounter uncertainty regarding the model's specification, incorporating learning approach to construct strategies based on Bayesian paradigm. Similarly, Kontosakos et al. (2024) used Bayesian approach to estimate the impact of return predictability and parameter uncertainty on long-term portfolio allocations. In comparison, dynamical Bayesian factor graph was proposed by the Wang et al (2015) to predict trend in the stock market. To sum up, these examples suggest that Bayesian setting was used in finance for various purpose, particularly, when it is relevant to address uncertainty in various forms, including model parameters and structures probabilistically. However, there isn't an extensive body of literature specifically focused on the application of change point detection in analyzing pension fund value dynamics, including Bayesian model, but some related studies that touch upon this topic indirectly have been published by many authors.

Methodology

To detect change points in the dynamics of PF value, Bayesian estimator of abrupt change, seasonal change, and trend (BEAST) was employed (Zhao *et al.*, 2019). This is a comparatively new approach, which was proposed to tackle the problem of conventional methods to focus on a singlebest-model paradigm, by neglecting the probable useful input of alternative models (e.g. Banner & Higgs, 2017; Koop, 2017). More specifically, BEAST is based on Bayesian approach, and therefore has a capacity to encompass every potential model, to assesses the likelihood of each model being accurate and combines numerous models to create an averaged model (Steel, 2020; Check & Piger, 2021; Zhao *et al.*, 2013). So, it is a multi-model approach, known as ensemble learning. The outcome of this model includes not only the timings and number of change points, but, more importantly, their likelihood over any given time. Additionally, the intensity level of change, whether high or low, is also estimated and expressed mathematically as the slope or derivative of the trend signal against the time.

Formally, a time series of historical observations $y_t, t = 1, \dots, n$ is additively decomposed into trend, seasonality, and noise, i.e.

$$y_t = T_t(\Theta_T) + S_t(\Theta_S) + \varepsilon_t; \tag{1}$$

where $T_t(\Theta_T)$ is the trend component with abrupt changes Θ_T, $S_t(\Theta_S)$ is the seasonal component with abrupt changes Θ_S, and ε_t is the noise, which is a stochastic variable distributed according to Gaussian distribution $\mathrm{N}(0, \sigma)$. In line with (Zhao *et al*., 2019), to simplify the demonstration, the parameters Θ_T and Θ_S are arranged into two groups, i.e. $\{\Theta_T, \Theta_S\} = \{\mathrm{M}, \beta_{\mathrm{M}}\}$. Here, M defines the model structure of number and timings of trend and seasonal changepoints including the seasonality model, while β_{M} refers to shapes of the trend and seasonality once the model structure M is known. Therefore, the time series decomposition given in Eq. 1 can be rewritten as:

$$y_t = x_M(t)\beta_M + \varepsilon_t; \tag{2}$$

where: x_M refers to dependent variables, with associated coefficients β_M.

In the Bayesian setting, given historical time series y_t, the most important step is to determine the posterior probability distribution $p(\beta_M, \sigma^2, \mathrm{M} \mid y_t)$, which is formally the product of a likelihood and a prior model, as given in (Zhao *et al*., 2019). To estimate the posterior distribution, a reverse-jump Markov Chain Monte Carlo (MCMC) algorithm is used to generate random simulations for posterior inference (Zhao *et al*., 2013). For a particular model $\mathrm{M}_{(\mathrm{i})}$, the generated chain encapsulates all the necessary dynamics, including trends, seasonal fluctuations, and abrupt changes. Combining the estimates of individual models $\mathrm{M}_{(\mathrm{i})}$, a final Bayesian model averaging (BMA) estimate is obtained as

$$\mathrm{E}(\hat{y_t}) \approx \tfrac{1}{\mathrm{N}} \textstyle\sum_{i=1}^{\mathrm{N}} x_{\mathrm{M}_{(i)}}(t)\, \beta_{\mathrm{M}_{(i)}}; \tag{3}$$

where: $\hat{y}_t$ denotes a statistical decomposition of historical data based on Equation 1. N is a number of models. The uncertainty measure is also determined in terms of variance using the formula

$$\mathrm{Var}(\hat{y_t}) \approx \frac{1}{\mathrm{N}-1} \textstyle\sum_{i=1}^{\mathrm{N}} (x_{\mathrm{M}_{(i)}}(t)\beta_{\mathrm{M}_{(i)}} - \mathrm{E}(\hat{y_t}))^2. \tag{4}$$

Finally, from the sampled chains, the number of change points in the trend or seasonal signals, as well as their timings of change occurred for each sampled mode$\mathrm{M}_{(i)}$ is determined. To sum up, the outcome of this algorithm, is the distribution of expected change points in the time-series dynamics as well as the timings with their credibility. The market stress were systematized by the authors are presented in Table 1. Identifying marginal change points is crucial to identify periods of overall shifts in the financial market. To achieve this, we compare these change points with dates of documented financial shocks and crises. Based on our findings, we focus our further analysis on the following periods.

Table 1

The Market Stress (Created by the Authors)

Period/date	**Notation**	**Description**
2007-2009	Global Financial Crisis	Financial turmoil: August 2007 to September 2008 and Global financial crisis: September 2008 to May 2010 (Montrimas *et.al*, 2023; Aparicio & Kim, 2023; Kok *et al.*, 2022).
2010-2015	Euro zone Debt Crisis	Euro area sovereign debt crisis: May 2010 to the second half of 2013. The low inflation phase: from August 2013 to January/February 2020 (Montrimas *et.al*, 2023; Kok *et al.*, 2022).
2011-2016	Emerging market Turmoil	Portuguese financial crisis (2010–2014); Cypriot financial crisis (2012–2013); Crisis in Venezuela (2012–now); Russian financial crisis (2014); Brazilian economic crisis (2014–2017) (Marsall, 2023; Serletis & Azad, 2020).
2015-2016	Chinese Stock market Crash	Chinese Stock market crash: 2015-06-12, the end 2016-01-19 (Maiello, 2019; AvaTrade, 2023; Salidjanova, 2016)
2016-06-23	Brexit Referendum	2016-06-23 (Hue *et al.*, 2019; Breinlich *et al.*, 2018)
2020-2023	COVID-19 pandemic	COVID-19 starts 2020-01-30, the end 2023-05-11 (HHS, 2023)
2022-ongoing	Russo- Ukrainian war	Russo- Ukrainian war started 2022-02-24 (Russia invaded Ukraine, 2023).

Investors use a variety of tools to assess the risk and return of investment vehicles. Therefore, the next step in our work is to evaluate performance of LT pension funds during market stress. In this paper is analysed: Mean return, Average Recovery, Appraisal ratio, Expected Shortfall, Information Ratio, Timing Ratio, Total (market) risk and Upside Potential. All they measure different aspects of market behaviour.

The Average Recovery estimates the average length (in periods) of the recovery period of the draw downs observed. Moreover, the recovery time or drawdown duration, labelled as Average Recovery, is determined as the average duration taken for recovery after draw downs observed.

The Timing ratio may help assess whether the manager is a good timer of asset allocation decisions (Hung & Jan, 2005). The ratio, which is calculated as:

$$\text{Timing ratio} = \frac{\beta^{+}}{\beta^{-}}, \quad (5)$$

is best when greater than one in a rising market and less than one in a falling market. Here, β^{+} is a regression for only positive market returns, while β^{-} is a regression for only negative market returns. The Timing Ratio uses the ratio of those to help assess whether the manager has shown evidence that of timing skill.

The Appraisal Ratio is computed by dividing Jensen's alpha by the specific/unsystematic risk (e.g., standard deviation of the residual), also referred to as the standard error of regression (Bacon, 2008). In this paper as measure of unsystematic risk we use specific risk (standard deviation) of asset. Alpha represents the excess return, calculated as the portfolio's return minus the return implied by the Capital Asset Pricing Model. The Appraisal Ratio serves as the ratio of active management returns to the risks associated with active management.

$$\text{Appraisal ratio} = \frac{Alpha}{Unsystematic\ risk}, \quad (6)$$

where: *Alpha* – rate of return a selection of stocks, *Unsystematic risk*- risk of the selection of stocks.

The Information ratio (IR) measures portfolio returns surpassing those of a benchmark (like the S&P 500) and relatives to the volatility of those returns. It serves as a metric for assessing a portfolio manager's ability to generate returns above a specified benchmark. The Information ratio is calculated as (Arora, 2015):

$$\text{IR} = \frac{(Portfolio\ Return\ -\ Benchmark\ Return)}{Tracking\ Error}, \quad (7)$$

where: *Portfolio return*- returns generated by the fund; *Tracking Error* - standard deviation of excess returns; *Benchmark return* - S&P 500 index.

Tracking error (TE) is one such tool used to evaluate the alignment between an investment's return and the benchmark, providing a measure of consistency over time in comparison to the benchmark (Kopa *et al.*, 2022). Utilizing Tracking error allows for the assessment of the disparity between the return variations of an investment portfolio and those of a selected benchmark. In this paper as a benchmark "S&P 500 index" was used and annualized TE calculated.

The Upside potential ratio (UPR) assesses the return of an investment asset in relation to the minimum acceptable return. This ratio enables pension funds to select investments with favourable upside performance relative to downside risk on a per-unit basis. The Upside potential ratio is calculated as (Coppitters & Contino, 2023):

$$\text{UPR} = \frac{Excess\ Return\ over\ MAR}{Standard\ Deviation\ of\ Returns\ below\ MAR} \quad (8)$$

The Upside Potential Ratio is calculated by dividing the excess return over a minimum acceptable return (MAR) by the standard deviation of returns below the MAR. In this paper MAR is set to 0, which is default value. All assets are compared to each other using the same MAR.

Total (market) risk includes both Systematic risk and Unsystematic risk and refers to the overall uncertainty associated with investing in any given asset or portfolio (Taylor, 2024):

$$\sigma_m = \sqrt{\sigma_{sys}^2 + \sigma_{spec}^2}, \quad (9)$$

where: σ_m - the total market risk, σ_{sys} - the systematic risk, and , σ_{spec} - the specific risk. Specific or unsystematic risk is risk of the selection of stocks.

The Expected Shortfall (ES) used to quantify the risk of a portfolio. This ratio measures the portfolio's loss when it exceeds the limit set by VaR (Taylor, 2022).

$$\text{Expected Shortfall} = \frac{1}{1-c}\int_{-1}^{VaR} xp(x)dx, \quad (10)$$

Where: $p(x)dx$ -the probability density of getting "x" return; c - the VaR cut-off point or breakpoint; *VaR* -the evaluated Value at the prespecified Risk level. Value-at-Risk (VaR) (Aleksander & Baptista, 2003) stands as an industry benchmark for assessing extreme risk.

Data and Limitations

For our research, we focus on Lithuanian pension funds managed by SEB and Swedbank that remained unchanged from 2004 to 2023. These two managers oversaw pension funds categorized by varying levels of risk, specifically between 2004 and 2018, the fund managers by their controlled funds by the underlying risk profile – from least risky bond funds to high-risk equity funds. SEB managed three funds: SEB1 (100 % bonds); SEB2 (50% equities, 50% bonds); SEB3 (100 % equities). Swedbank managed four funds: SWED1 (100 % bonds); SWED2 (up to 70 % bonds); SWED3 (up to 70 % equities); SWED4 (100 % equities).

In 2019, the pension system underwent reforms, transitioning to life cycle funds. Both SEB and Swedbank managers now oversee eight pension funds each, categorized by the same level of risk. These funds are classified into four groups based on investment strategy, with most second pillar pension funds being "mixed," investing in both high-risk (e.g., equities) and less risky (e.g., government bonds) asset classes (Bank of Lithuania, 2023). Assets in these funds are managed based on the target group participants' birth year, ranging from 1954 to 2002 (1954-1960; 1961-1967; 1968-1974; 1975-1981; 1982-

1988; 1989-1995; 1996-2002). Different pension fund strategies are presented in Figure 1.

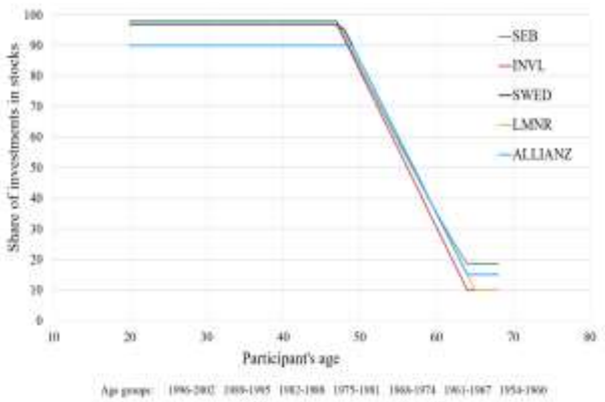

Figure 1. Strategy of Life-Cycle Pension Funds (PFs) Adopted Since 2019

To conduct our study, we selected four life cycle pension funds corresponding to the risk levels of pension funds operational until 2018. Specifically, SEB3 corresponds to SEB 1996-2002; SEB2 corresponds to SEB 1968-1974; SEB1 corresponds to SEB 1961-1967; and SEB1 corresponds to SEB 1954-1960. Similarly, SWED4 corresponds to SWED 1996-2002; SWED3 corresponds to SWED 1968-1974; SWED2 corresponds to SWED 1961-1967; and SWED1 corresponds to SWED 1954-1960.

Results

To identify periods of significant shifts in the financial market, we examine the marginal change points in pension funds with varying risk profiles during the initial period of 2004-2018. Throughout this timeframe, the conservative fund SEB 1, comprising solely of government bonds, exhibited gradual growth from 0.3 to 0.38 percent. Structural point changes (with a probability of change equal to 1) were observed in October 2008 and August 2009, coinciding with the European debt crisis and the Emerging market turmoil. Notably, in May 2015, during these crises, the estimated probability curve displayed numerous minor peaks alongside a significant peak (probability of change = 0.7). The value of the SEB 1 fund primarily responded to the global financial crisis and its aftermath. Conversely, the reactions of the conservative fund SWED 1 were distinct, with structural shocks identified in February 2015, June 2015, and notably after the Brexit referendum in November 2016 (see Figures 2-5). SWED 2, which included up to 30 percent equities, exhibited different reactions compared to SWED 1. High-intensity shifts occurred during the Global financial crisis in June 2006, October 2007, and October 2008. A probability of change point was identified in June 2013 during the European debt crisis and Emerging market turmoil. When assessing riskier pension funds, similar trends were observed for SEB 2 and SWED 3, as well as for SEB 3 and SWED 4.

Structural point changes in the riskiest pension funds, SWED4 and SEB3, were identified in October 2008, with a recovery observed in May 2009 for SWED 4 and April 2009 for SEB 3. Until February 2011, there was a low likelihood of abrupt changes in the price trend, but a rapid and significant decrease was observed in August 2011, followed by minimal disturbance until 2015. Change points were identified in both SWED4 and SEB3 in February and August 2015, and January 2016 during the Chinese stock market crash. Pension funds SWED3 and SEB2, where equities accounted for up to 70 percent, demonstrated identical behaviour. Both funds experienced a sharp decline in October 2008, a recovery in April 2009, and slight declines in August 2011 and June 2013. Change points were identified in both SWED3 and SEB2 in February and August 2015, and January 2016 during the Chinese stock market crash. Interestingly, equity funds did not react significantly to the Brexit referendum, indicating a low likelihood of abrupt changes in the price trend.

When evaluating the value of life cycle pension funds during the period of 2019-2023, similar trends in value change points were observed. Both SWED 54-60 and SEB 54-60 pension funds reacted to the Covid-19 pandemic only in March 2020, with value disturbances persisting until December 2021. Similarly, during the Russo-Ukrainian war, both pension funds exhibited reactions in January 2022, October 2022, and October 2023, with high probability change points identified. Analysing higher-risk (96-02, 68-74, and 61-67) life cycle SEB and SWED pension funds revealed similar value change trends. A sharp decline was observed in March 2020 in all pension funds, followed by a period of value recovery until January-February 2022. Subsequently, there was a decline in value until October 2022, with small peaks in the estimated probability curve until the end of 2023, indicating a low likelihood of abrupt changes in the price trend. Notably, the probability of value recovery in May 2022 was determined in both SWED 61-67 and SEB 61-67 pension funds, as well as in the highest-risk SEB 96-02 pension fund.

In summary, both riskier and conservative pension funds exhibited similar behaviours during the Covid-19 pandemic, Russo-Ukrainian war, and Brexit periods, independent of fund managers. However, this similarity does not extend to financial market stress during the Global Financial Crisis, Euro zone Debt Crisis, Emerging market Turmoil, and Chinese Stock Market Crash. Based on the received analysis data, using the change point detection technique and applying Bayesian averaging (Zhao et al., 2019), periods of different market behaviour in 2007-2023 were determined (see Table 2).

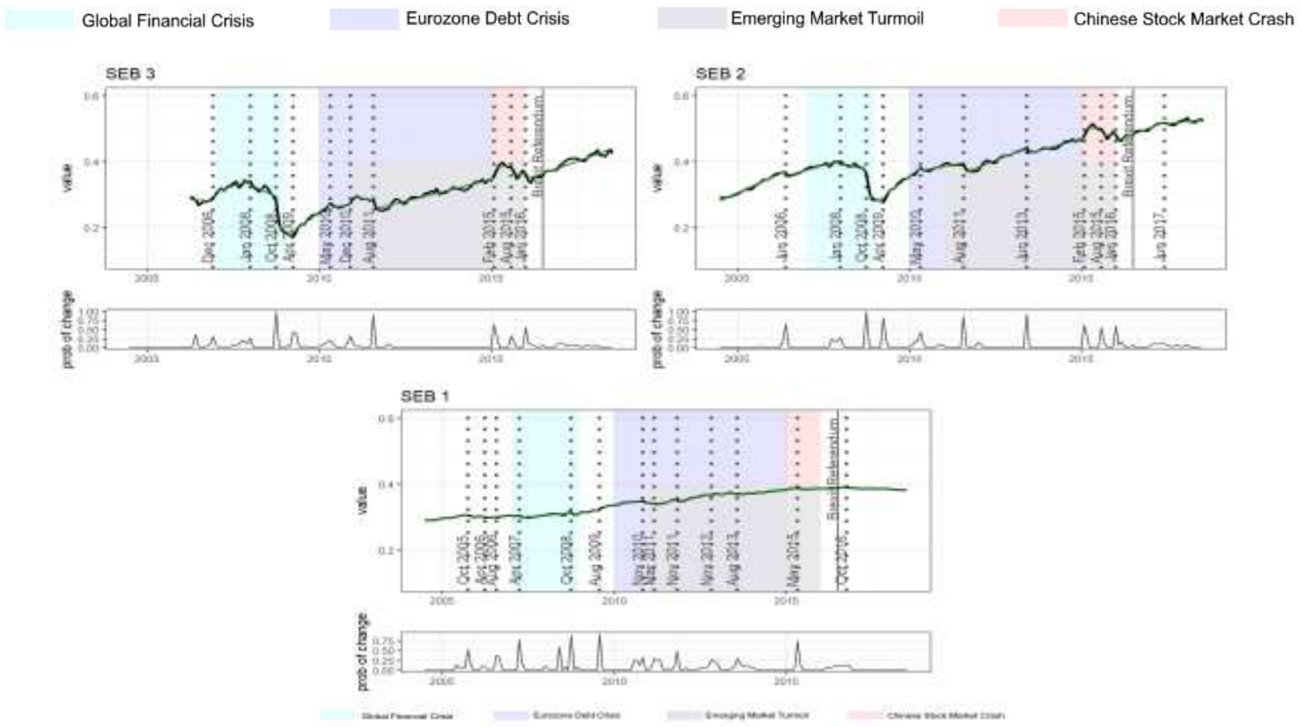

Figure 2. Change Points SEB Pension Funds During 2004-2018 (Created by the Authors)

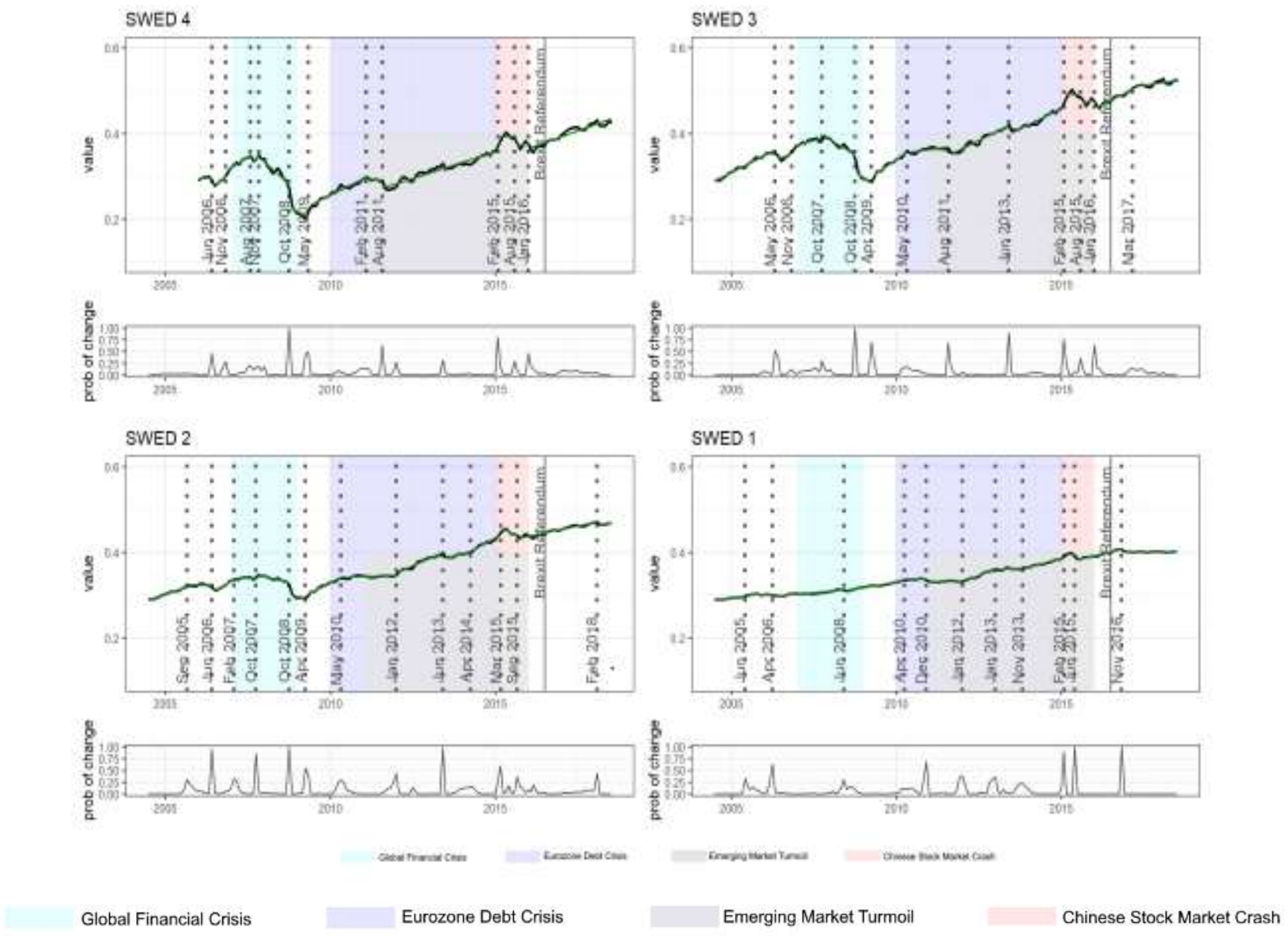

Figure 3. Change Points Swedbank Pension Funds During 2004-2018 (Created by the Authors)

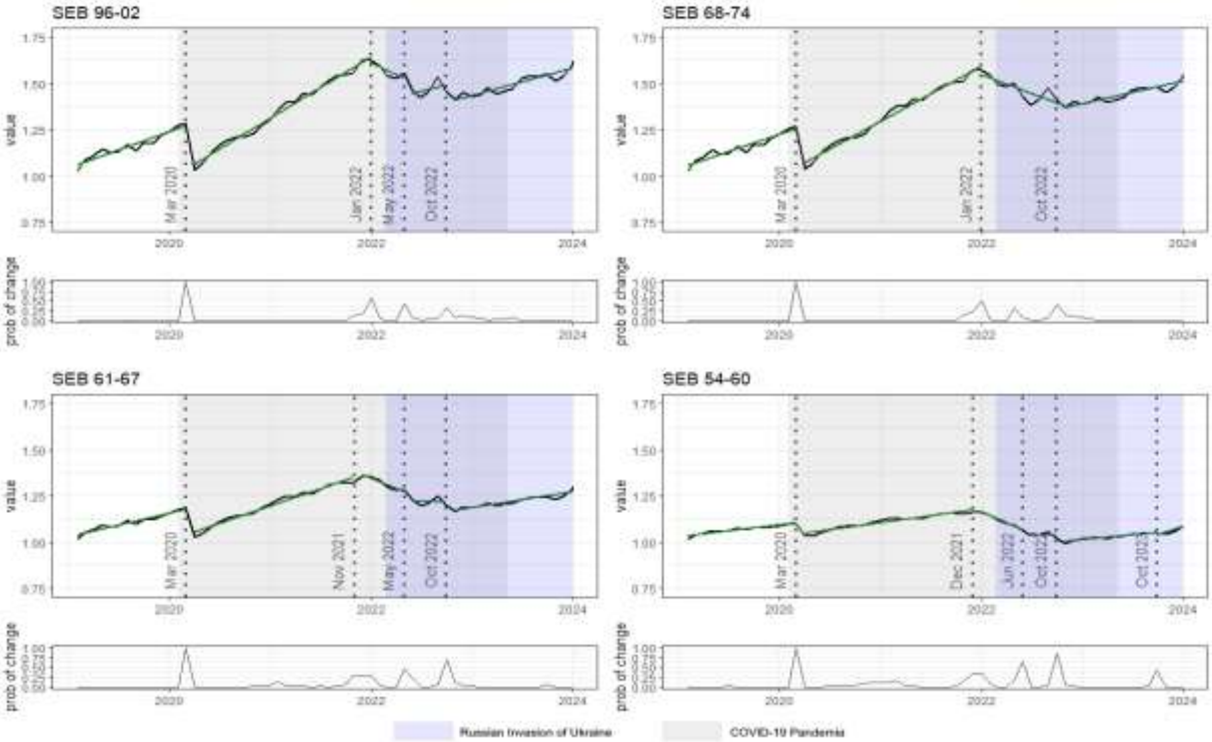

Figure 4. Change Points Life-Cycle SEB Pension Funds During 2019-2023 (Created by the Authors)

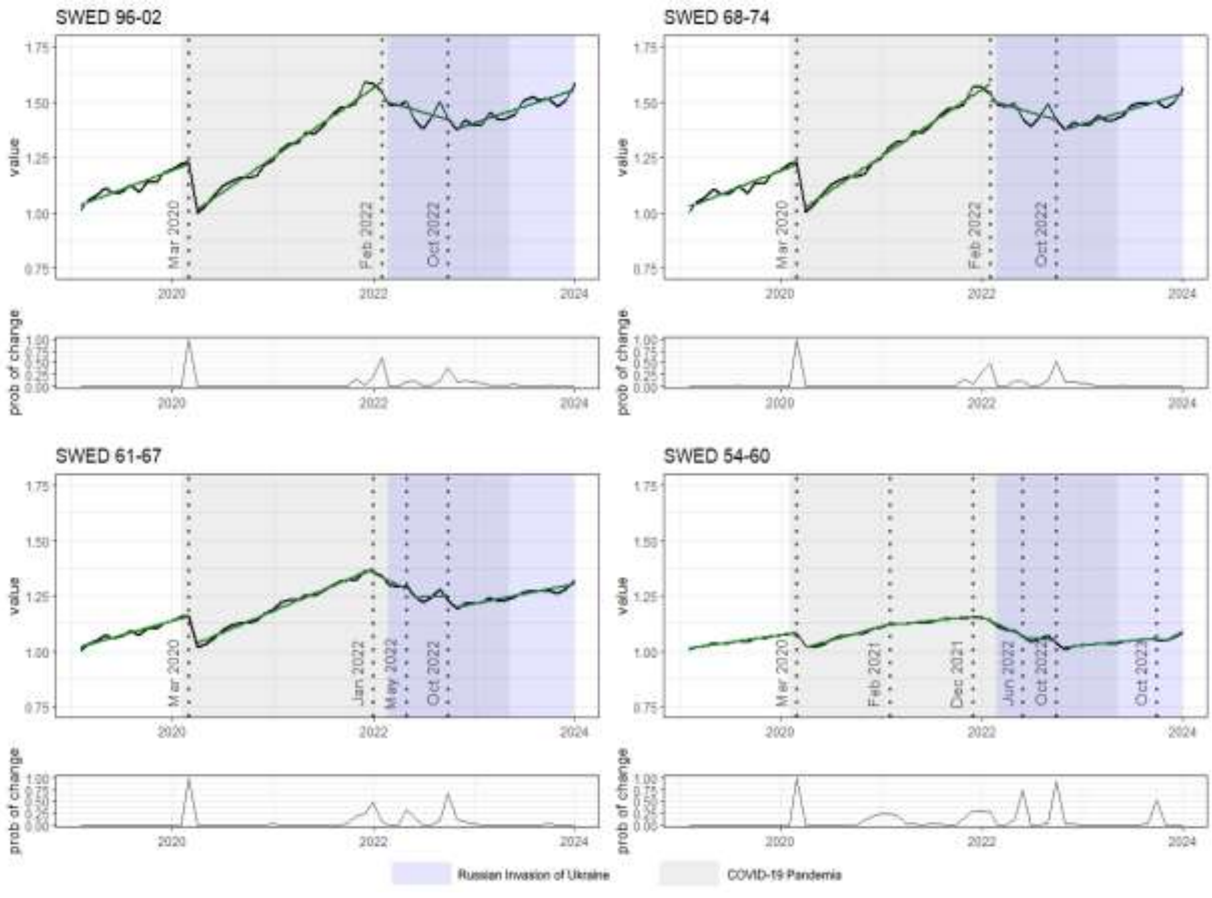

Figure 5. Change Points Life-Cycle Swedbank Pension Funds During 2019-2023 (Created by The Authors)

Table 2

Periods of Different Market Behaviour in Period 2007-2023 (Created by the Authors)

Period	Market events and response of pension funds
2007-08-01 - 2009-03-31	Financial turmoil and global Financial Crisis. Severe drop in market value.
2009-04-01 - 2010-02-28	Global financial crisis. Recovery of global markets observed. Pension funds recovered 2 months earlier.
2010-03-01 - 2011-07-31	Euro zone Debt Crisis; Emerging market Turmoil. Pension funds reacted 2 months earlier. In 2010 the Portuguese crisis began. The Asian crisis began in January 2011.
2011-08-01 - 2015-01-29	Rapid market growth; Greek debt crisis first stress until 2013, second stress from July 2014. The Portuguese crisis continues until 2014. 2012 started the Cypriot financial crisis and finished 2013. Russian invasion to Ukraine 2014. Russian financial crisis. 2014 started Brazilian economic crisis.
2015-02-01 - 2015-12-31	Chinese Stock market crash. Shocks in global markets. Pension funds reacted 4 months earlier.
2016-01-01 - 2018-12-31	Brexit referendum in UK; Crypto currency crash; Elections in the USA. Pension funds reacted 6 months earlier.
2019-01-03 - 2020-02-27	Stable growth in all markets.
2020-03-02 - 2021-10-28	COVID-19 starts and recovers.
2021-11-03 - 2022-09-29	Russia deploys large groups of armed forces close to Ukrainian border. Russo- Ukrainian war started in 2022-02-23. Russian market crash. Pension funds reacted 3 months earlier.
2022-10-03 - 2023-12-28	Russo- Ukrainian war continues. Recovery of markets starts

The Mean return of pension funds serves as a metric, representing the average return achieved by the fund over a specified period. It is instrumental in assessing the fund's performance against its investment objectives and understanding the incurred gains or losses. The range of mean returns for pension funds typically falls close to zero, as observed in the data presented (ranging from -0.0016 to +0.0016). The proximity to zero suggests a relatively stable investment performance with minimal growth or losses, as illustrated in Figure 5

Mean return SEB and Swedbank pension funds 2004-2018	Mean return SEB and Swedbank life-cycle pension funds 2019-2023

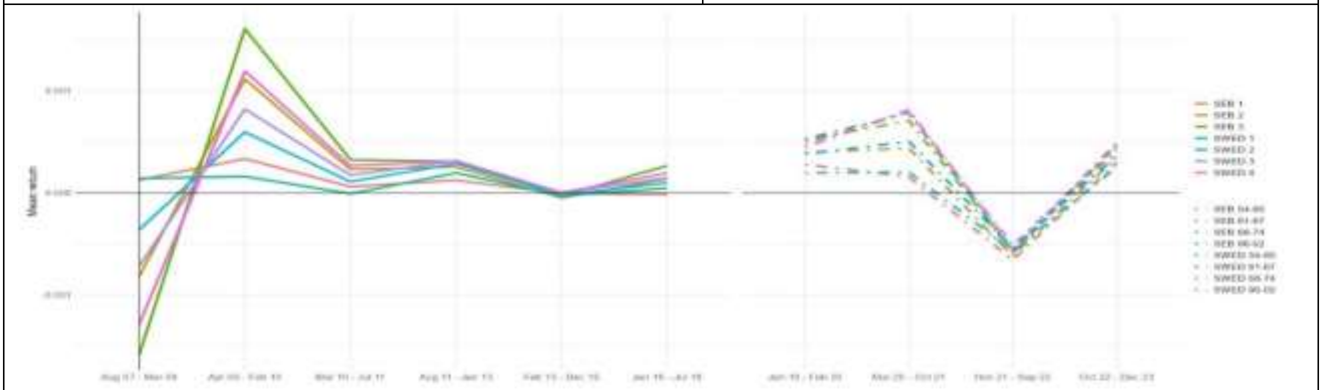

Figure 5. SEB and Swedbank Pension Funds *Mean Return* During 2004-2018 and 2019-2023 (Created by the Authors)

Notably, during the global financial crisis, pension funds SEB3 and SWED4 experienced significant decreases followed by substantial recoveries, indicating resilience amid market turmoil. Conversely, conservative pension funds (SEB1 and SWED1) maintained positive returns during this period, reflecting their risk-averse nature. A notable event was the Chinese Stock market crash (between 2015-02-01 and 2015-12-31), during which all funds, regardless of risk profile, exhibited declines, with mean return values again nearing zero. Life cycle pension funds experienced a sharp decline (-0.0005) preceding the Russo-Ukrainian war (between 2021-11-03 and 2022-09-28) but rebounded similarly afterwards (between 2022-10-03 and 2023-12-28). Although the negative return was relatively small, it demonstrates the importance of robust risk management and the potential impact of geopolitical tensions or economic downturns on investment performance. In periods of minimal returns during market stress, such as observed, it suggests that the pension fund's investments yielded modest profits on average, except during major crises like the global financial crisis and the Chinese Stock market crash. Investors may interpret this as a sign of stable but conservative performance, particularly during challenging market conditions. This modest growth, albeit conservative, contrasts favourably with negative returns or stagnant growth, highlighting the efficacy of the fund's investment strategies. Moving forward, there's a clear indication for pension funds to reassess their investment strategies and asset allocations, particularly in mitigating losses and enhancing future returns. Adaptation to market dynamics and proactive risk management remain imperative for sustaining favourable investment outcomes amid evolving economic landscapes.

Average recovery SEB and Swedbank pension funds 2004-2018	Average recovery SEB and Swedbank life-cycle pension funds 2019-2023

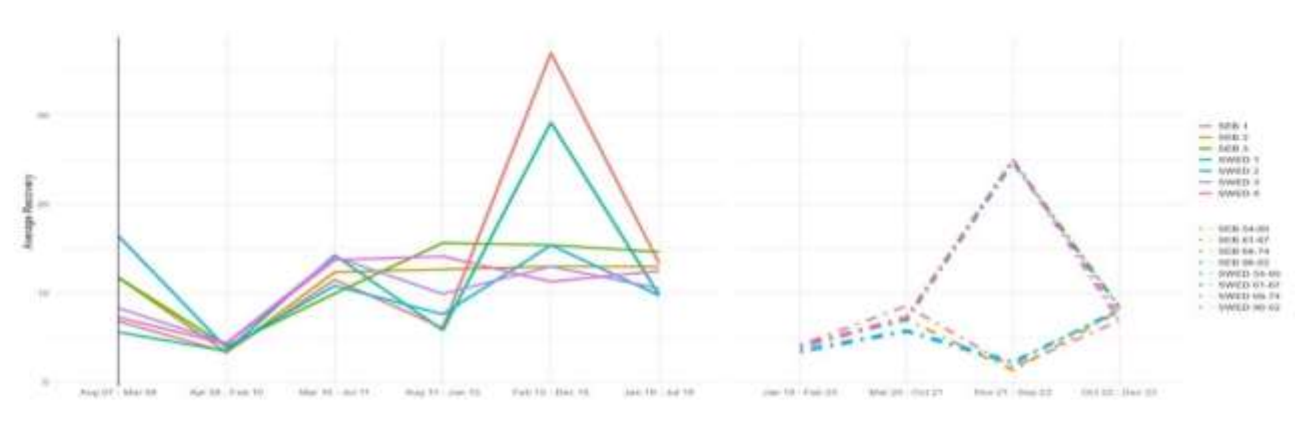

Figure 6. SEB and Swedbank Pension Funds *Average Recovery* During 2004-2018 and 2019-2023 (Created by the Authors)

The Average recovery of pension funds is a pivotal metric, representing the percentage growth of an investment portfolio from its preceding downturn to a subsequent high or profitable level. It elucidates the extent to which the pension fund rebounds, on average, following each downturn. The variability in Average recovery underscores the influence of factors such as investment strategy, risk tolerance, and prevailing market conditions.

During the global financial crisis, all pension funds experienced Average recovery rates ranging from 5 to 17 percent, with SWED2 pension fund exhibiting the highest growth at 17 % (refer to Figure 6). This signifies a mild post-recession portfolio growth and implies subdued portfolio profitability or constrained potential for growth. Notably, there is a stark contrast in the recovery between conservative and riskier pension funds. Amidst global market shocks, SWED1 and SEB1 achieved robust recoveries of 28 and 43 percent, respectively, indicating a significant bounce-back. It's noteworthy that these funds had encountered a 5 % recession in the preceding period marked by rapid market growth. Conversely, the more conservative funds (SEB2, SEB3, SWED3, and SWED4) maintained relatively stable positions during this period. Another noteworthy period emerged before the Russo-Ukrainian war, during which all four of the riskiest life-cycle funds managed by different managers (SEB and SWED 96-02; 68-74) achieved recoveries of up to 25 percent. This suggests that equity pension funds exhibit a notably higher propensity for recovery during such periods of upheaval. However, in the subsequent period of market recovery (between 2022-10-03 and 2023-12-28), these funds experienced the most significant declines, regressing to a 5 % profitability level, mirroring the trajectory observed across other pension funds.

These fluctuations underscore the dynamic nature of pension fund performance and the impact of external events on recovery prospects. Moving forward, it's imperative for pension fund managers to adapt their strategies to navigate through periods of market volatility effectively and capitalize on opportunities for sustainable growth and profitability.

Appraisal Ratio SEB and Swedbank pension funds 2004-2018	Appraisal Ratio SEB and Swedbank life-cycle pension funds 2019-2023

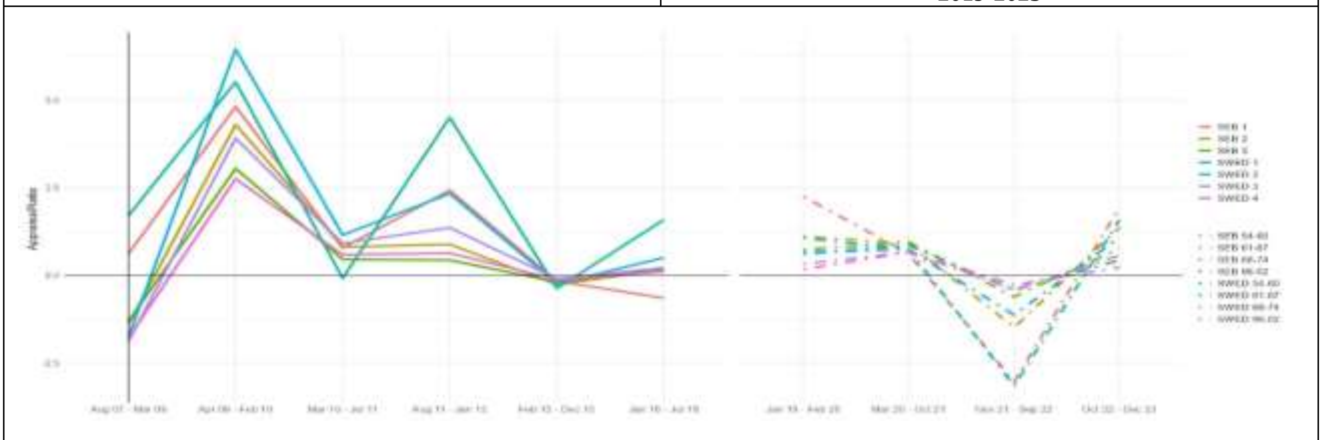

Figure 7. SEB and Swedbank Pension Funds *Appraisal Ratio* During 2004-2018 and 2019-2023 (Created by the Authors)

The Appraisal ratio yields diverse insights across select periods, notably during the Global Financial Crisis (between 2007-08-01 and 2009-03-31), Chinese Stock market crash (between 2015-02-01 and 2015-12-31), and pre-Russo-Ukrainian war (between 2021-11-03 and 2022-09-29). Low appraisal ratios observed during these periods imply suboptimal fund management, indicating that funds assumed significant risk to achieve returns. Comparing the fund's alpha, representing the excess return earned over the benchmark, to the residual standard deviation revealed that all pension fund managers (excluding SWED1 and SEB1 during the global financial crisis) generated negative units of active return per unit of risk, particularly pre-Russo-Ukrainian war. However, in other periods, fund managers exceeded the performance of their passive portfolio benchmark without exposing investors to undue stress from excessive risk or volatility. Notably, during the Global Financial Crisis, the riskiest pension funds managed by SEB1 and SWED1 maintained positive returns, indicative of optimal fund management during this tumultuous period. Conversely, during market recovery periods (between 2009-04-01 and 2010-02-28 and between 2011-08-01 and 2015-01-29), SWED1 and SWED2 fund managers surpassed their passive portfolio benchmark, yielding the highest returns.

Considering total (market) risk is crucial for pension fund managers in decision-making and portfolio management. Various risk management strategies can help mitigate its impact. Assessment of total market risk reveals relatively stable market conditions with minor directional changes across analysed periods, except during the global financial crisis. Notably, during this period and the pandemic period, the riskiest pension funds such as SWED4, SEB3, and SWED 68-74 stood out the most, indicating heightened market instability and risk exposure (see Figure 8).

Total (market) risk SEB and Swedbank pension funds 2004-2018	Total (market) risk SEB and Swedbank life-cycle pension funds 2019-2023

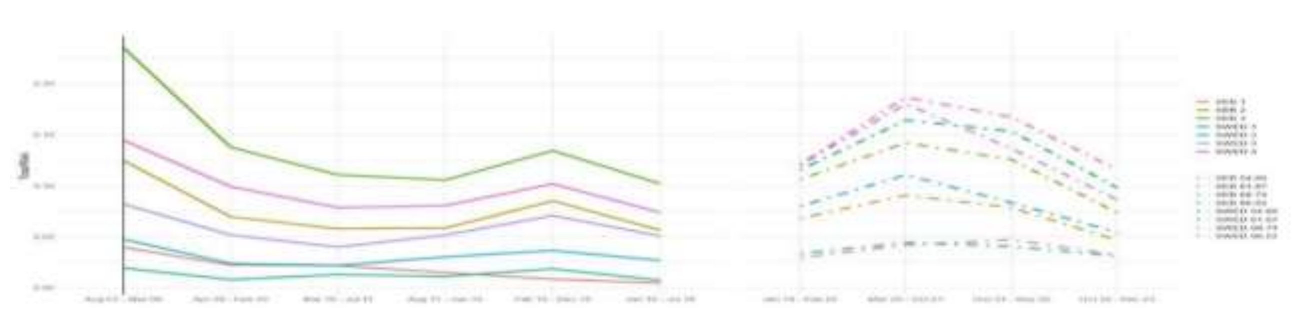

Figure 8. SEB and Swedbank Pension Funds *Total (Market) Risk* During 2004-2018 and 2019-2023 (Created by the Authors)

The most volatile periods were identified during the Global Financial Crisis (between 2007-08-01 and 2009-03-31), Chinese Stock market crash (between 2015-02-01 and 2015-12-31), the onset and recovery of COVID-19 (between 2020-03-02 and 2021-10-28), and preceding the Russo-Ukrainian war (2021-11-03 and 2022-09-29). In these periods, the riskiest pension funds managed by both pension fund managers (SEB3 and SWED4) recorded their highest values. Elevated total market risk values signify a more aggressive investment strategy and an equity-heavy portfolio. The values of the most conservative life cycle funds hovered around 0.05, indicating relatively low market risk for the pension fund. This implies that these pension fund investments are less volatile and possess lower exposure to market fluctuations. Such stability and predictability in the pension fund's performance, exemplified by funds like SEB 54-60 and SWED 54-60, suggest smaller potential losses during market downturns. This underscores the resilience of these conservative funds and their ability to weather turbulent market conditions while providing stability to investors

Upside Potential ratio SEB and Swedbank pension funds 2004-2018	Upside Potential ratio SEB and Swedbank life-cycle pension funds 2019-2023

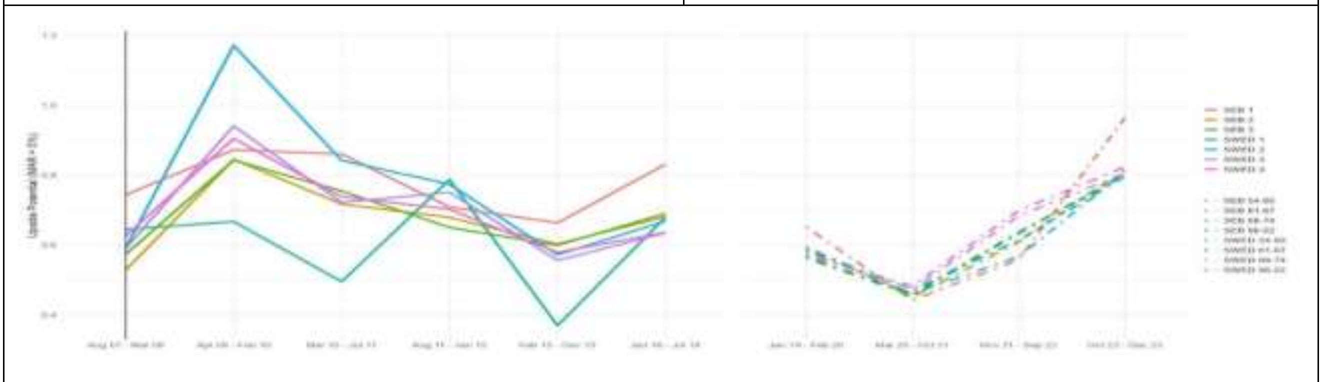

Figure 9. Upside Potential Ratio SEB and Swedbank Pension Funds *Upside Potential Ratio* During 2004-2018 and 2019-2023 (Created by the Authors)

The Upside Potential ratio (Moller & Pillay, 2014) provides a probability-weighted average above a specified threshold rate. This ratio is relevant for investors seeking assets or funds with greater potential for upside gains compared to their downside risk. Such insights are instrumental in portfolio construction and asset allocation strategies. It's worth noting that SEB and SWED pension fund managers operated differently during the period from 2007 to 2018 compared to when managing life cycle pension funds. The most conservative pension funds, such as SWED1 and SWED2, exhibited significant deviations during periods of market stress, ranging from 0.3 to 1.1. These ratios indicate that for every unit of downside risk taken, the fund can capture 0.3 to 1.1 units of upside potential, showcasing their ability to capture upside potential relative to downside risk. During periods of market stress, the life cycle funds of all pension fund managers performed similarly in both recoveries and downturns. However, SEB 54-60 stands out, particularly during the recovery period, exhibiting the highest values. A higher ratio for this pension fund suggests that SEB 54-60 has the potential to generate significant returns during favourable market conditions relative to the level of risk it assumes. This highlights the fund's ability to capitalize on upside opportunities while managing downside risk effectively.

Timing Ratio SEB and Swedbank pension funds 2004-2018	Timing Ratio SEB and Swedbank life-cycle pension funds 2019-2023

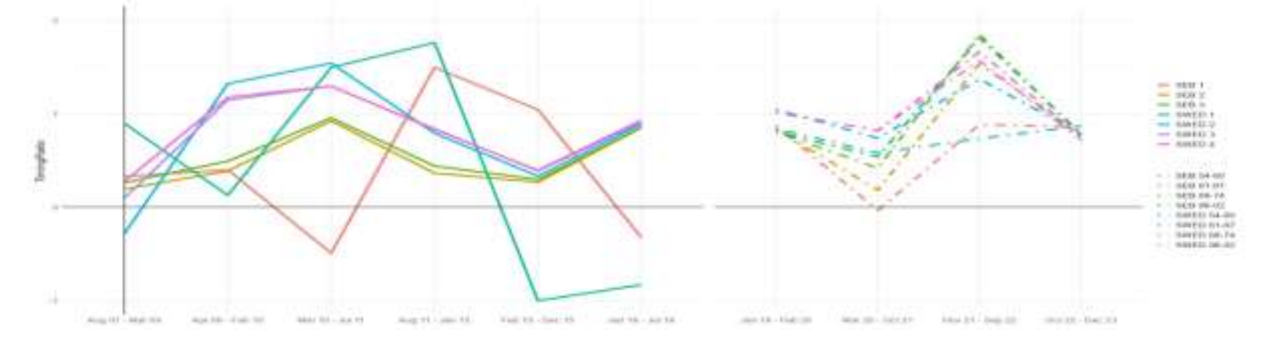

Figure 10. SEB and Swedbank Pension Funds *Timing Ratio* During 2004-2018 and 2019-2023 (Created by the Authors)

Timing ratio provides insight into how well the fund investment decisions align with market movements. It has been observed that the Timing ratio values of conservative pension funds exhibited considerable fluctuations, ranging from -1 to 2, without a consistent trend of change across different periods of market stress (see Figure 10). Notably, negative values for conservative pension funds like SWED1, SWED2, and SEB1 indicate that their investment timing has been contrary to market movements. This suggests a tendency to buy assets before their prices decline and sell them before their prices rise, resulting in losses or underperformance compared to the market, particularly evident during crises such as the European sovereign bond crisis and the Chinese Stock market Crash. This trend is particularly pronounced in the cases of SEB1 and SWED1. Conversely, the positive Timing ratio values for the riskiest pension funds (SWED3 and SWED4) indicate that SWED's fund managers tend to buy assets before their prices rise and sell them before their prices decline, resulting in outperformance compared to the market. However, the same cannot be said for SEB's pension fund managers. In contrast, life-cycle funds exhibited consistent positive Timing ratio values during all periods of market stress. This suggests that the life-cycle funds managed by both SEB and SWED are efficiently managed, attracting investors seeking actively managed funds with stronger performance relative to the market. This indicates a more strategic and effective approach to investment timing, enhancing the funds' ability to navigate market fluctuations and capitalize on opportunities for growth.

Information ratio SEB and Swedbank pension funds 2004-2018	Information ratio SEB and Swedbank life-cycle pension funds 2019-2023

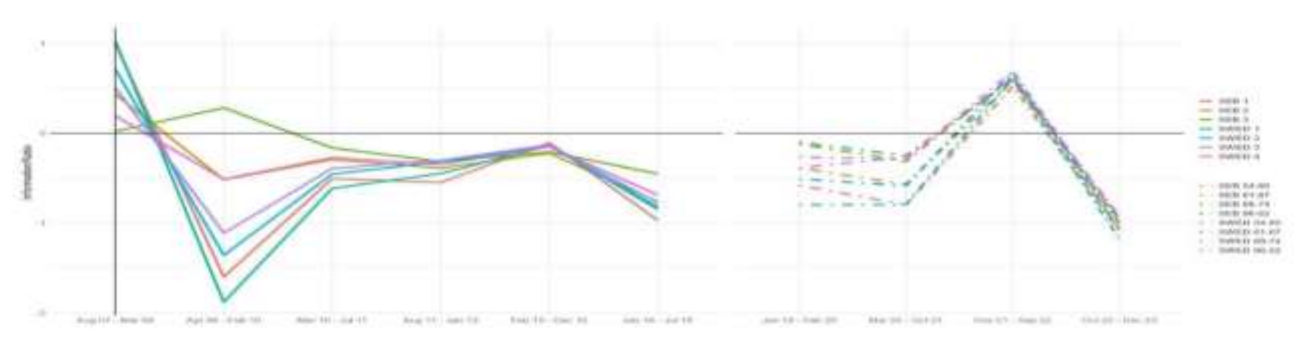

Figure 11. SEB and Swedbank Pension Funds *Information Ratio* During 2004-2018 and 2019-2023 (Created by the Authors)

The Information Ratio serves as a measure of how effectively the fund's active management performance compares to the S&P 500 index, acting as a benchmark. Negative Information Ratios observed in all old pension funds (except SEB3) during most market stress periods (excluding periods between 2007-08-01 and 2009-03-31 and between 2021-11-03 and 2022-09-29) suggest that the fund's active management decisions have detracted value compared to simply holding the benchmark. Specifically, during the global financial crisis, Information Ratio values for conservative pension funds SWED1, SWED2, SEB1, and the riskier SWED3 fluctuated between -1 and -2. This indicates that for each unit of risk taken, the pension funds generated one to two units less return than the benchmark. Notably, just before the start of the Russian invasion of Ukraine, all life cycle funds reached a value of 0.7. This can be interpreted as a positive signal of effective active management and the ability of the fund to generate excess returns during this period. It's crucial to note that this positive signal was short-lived, as subsequent periods saw a drop in Information Ratio values for all pension funds until they reached -1 again, indicating underperformance by pension fund managers. This underscores the challenges faced by pension fund managers in consistently outperforming the benchmark and highlights the need for ongoing evaluation and adjustment of active management strategies.

Discussion

In our research, we've uncovered a significant research gap pertaining to the lack of comprehensive insights into pension fund performance and strategies under various market stresses. The prospectus, approved by each country's governing body (e.g., the Bank of Lithuania in Lithuania), serves as a crucial document outlining pension fund management, including key characteristics such as pricing, investment areas, and strategies. Adjustments in fund asset allocation are governed by two main strategies: strategic asset allocation, which defines key markets and is typically reviewed annually, and tactical asset allocation, specifying particular sectors and usually reviewed monthly. Tactical asset allocation primarily guides investment operations, although it generally doesn't involve drastic adjustments. Significant changes in the investment strategy, such as altering the share of risky and less risky assets by more than 5 percentage points, require a thorough review and evaluation of the strategy at least once every three years (Bank of Lithuania, 2018). However, our research uncovered that only life-cycle funds adhere to such a strategy.

By assessing the reaction of pension funds to different market stresses, we observed that pension funds tend to react a few months earlier to already identified market events. However, it becomes challenging to ascertain the behaviour of pension funds when multiple market stresses occur simultaneously, such as during the Euro zone Debt Crisis or Emerging Market Turmoil. Therefore, future studies should delve into such specific events during market stress periods. To evaluate pension fund performance during market stress, we selected indicators that are interrelated but measure different aspects of pension fund behaviour, drawing from indicators used by other researchers. Total risk and Upside Potential indicators are related to risk management. Total risk quantifies the total risk involved in pension fund investments, while Upside Potential indicates the potential return that can be achieved over a period of time regardless of risk.

While the chosen indicators are crucial for pension fund managers and investors seeking to evaluate pension fund performance and make informed investment decisions, we acknowledge that they may not fully capture the performance of pension funds. Hence, it's essential to assess performance using a diverse range of indicators. Nonetheless, we argue that our results shed light on pension fund responses to market stress, as we examined both profitability and risk management measures.

Conclusions

Assessing the performance of pension funds during crises is crucial for understanding their capacity for risk management, flexibility, and overall competence in generating returns amid challenging market conditions. Total market risk assessment aids pension fund managers in evaluating risk exposure and making informed decisions to achieve their investment objectives. The Bayesian averaging approach yields the distribution of expected change points in time-series dynamics, along with their probabilities. Metrics such as draw downs, recovery rates, and timing ratios are particularly valuable for assessing pension fund performance during crises and market disturbances. Pension fund asset allocation for participants nearing retirement age typically favours safer and less volatile financial instruments, aiming to limit potential losses during periods of short-term market volatility. However, it's important to acknowledge that no pension funds are entirely shielded against negative returns, as uncertainty can persist for indeterminate periods, with unforeseen effects on the global economy. No pension fund is entirely shielded from negative returns due to market fluctuations, interest rates, inflation, and other factors. Even the Lithuanian 2nd pillar's restriction on risky assets like stocks can't eliminate risk entirely, as other investments like bonds can still experience losses. Moreover, options are not welcome according to Lithuanian regulation. During crises, the duration and severity of a recession depend partly on the complexity of the economic crisis triggered by market stress, and how countries, governments, and populations respond to subsequent market developments. While short-term market volatility may adversely impact fund returns, pension funds typically maintain a long-term outlook. Consequently, such deviations may hold less significance over the longer horizon.

Acknowledgment

This project has received funding from the Research Council of Lithuania (LMTLT), agreement No. S-MIP-21-32.

References

Alexander, G. J., & Baptista, A.M. (2003). Portfolio Performance Evaluation Using Value at Risk. *Journal of Portfolio Management*, 24(4), 93–102. https://doi.org/10.3905/jpm.2003.319898

Angulo, A. M., Mur, J., & Trivez, F. J. (2018). Measuring resilience to economic shocks: an application to Spain. The Annals of Regional Science, 60, 349–373. https://doi.org/10.1007/s00168-017-0815-8

Aparicio, K., & Kim, R. (2023). External capital market frictions, corporate governance, and tax avoidance: Evidence from the TED spread. *Finance Research Letters*, 52, 103381. https://doi.org/10.1016/j.frl.2022.103381

Arora, K. (2015). The Information Ratio on Indian Mutual Funds**.** *Journal of Management Research*, 7**(**1**)**, 34-42**.** Available from internet: https://www.researchgate.net/publication/349728644_The_Information_Ratio_on_Indian_Mutual_Funds

Autene, A., Degoli, M.C., & Hartmann-Cortes, K. (2021). Introduction to the Special Issue on Sustainable Pensions: Do Sustainable Pensions Require Sustainable Investments? *European Journal of Social Security*, 23(3). https://doi.org/10.1177/13882627211038965

AvaTrade (2023). The 2015-16 Chinese Market Crash. Available from internet: https://www.avatrade.com/blog/trading-history/the-2015-16-chinese-market-crash

Bacon, C.R. (2008). Practical portfolio performance measurement and attribution, Second edition. 2008 John Wiley & Sons Ltd. https://doi.org/10.1002/9781119206309

Badea, L., Armeanu, D. S., Panait, J., & Gherghina, C. S. (2019). A Markov Regime Switching Approach towards Assessing Resilience of Romanian Collective Investment Undertakings. *Sustainability*, 11(5), 1325; Available from internet: https://doi.org/10.3390/su11051325

Bank of England. (2014). Procyclicality and structural trends in investment allocation by insurance companies and pension funds: A Discussion Paper by the Bank of England and the Procyclicality Working Group. Available from internet: https://www.bankofengland.co.uk/-/media/boe/files/paper/2014/procyclicality-and-structural-trends-in-investment

Bank of Lithuania. (2018). Bank of Lithuania. Lyginamu ju ̧indeksu ̧naudojimo taisykl ́es, 2012. Decision nr. 03-155 (2012-06-12): format/ISO_PDF, Vilnius Available from internet: https://e-seimas.lrs.lt/rs/legalact/TAD/TAIS.430469/.

Bank of Lithuania. (2023). Available from internet: https://www.lb.lt/lt/pf-veiklos-rodikliai

Banner, K. M., & Higgs, M.,D. (2017), Considerations for assessing model averaging of regression coefficients. *Ecol Appl*, 27, 78-93. https://doi.org/10.1002/eap.1419

Bessembinder, H., Cooper, M. J., & Feng, Z. (2022). Mutual Fund Performance at Long Horizons. *Journal of Financial Economics (JFE), Forthcoming*, 1-70. Available from internet: https://doi.org/10.2139/ssrn.4096205

Breinlich, H., Leromain, E., Novy, D., & Sampson, T. (2018). The Economic Effects of Brexit: Evidence from the Stock Market. *Fiscal Studies*, 39(4), 581–623. https://doi.org/10.1111/1475-5890.12175

Check, A., & Piger, J. (2021), Structural Breaks in U.S. Macroeconomic Time Series: A Bayesian Model Averaging *Approach. Journal of Money*, Credit and Banking, 53, 1999-2036. https://doi.org/10.1111/jmcb.12822

Chen, H., Ju, N., & Miao, J. (2014). Dynamic asset allocation with ambiguous return predictability. *Review of Economic Dynamics*, 17(4), 799-823. https://doi.org/10.1016/j.red.2013.12.001

Coppitters, D., & Contino, F. (2023). Optimizing upside variability and antifragility in renewable energy system design. *Scientifc Reports*, 13, 9138. Available from internet: https://doi.org/10.1038/s41598-023-36379-8

Duijm, P., & Bisschop, S. S. (2015). Short-termism of long-term investors? The investment behaviour of Dutch insurance companies and pension funds, *DNB Working Paper*, 489. Available from internet: https://www.dnb.nl/media/3slnenht/working-paper-489.pdf; https://doi.org/10.2139/ssrn.2762200

Fama, E. F., & French, K. R. (2017). Long-Horizon Returns 2017. *Chicago Booth Research Paper*, 17(17), Fama-Miller Working Paper, Available from internet: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2973516;

https://doi.org/10.2139/ssrn.2973516

Gonzalez, A. T., van Lelyveld, I., & Lucivjanska, K. (2020). Pension fund equity performance: Patience, activity or both*?*, *Journal of Banking & Finance*, 115(C). Available from internet: https://www.sciencedirect.com/science/article/abs/pii/S0378426620300790; https://doi.org/10.1016/j.jbankfin.2020.105812

Gupta, M., Wadhvani, R., & Rasool, A. (2024). Comprehensive analysis of change-point dynamics detection in time series data: A review. *Expert Systems with Applications*, 248, 123342. https://doi.org/10.1016/j.eswa.2024.123342

Habibi, R. (2021). Bayesian online change point detection in finance, *Financial Internet Quarterly*, 17 (4), 27-33. https://doi.org/10.2478/fiqf-2021-0025HHS. (2023). U.S. Department of Health and Human Services. Available from internet: https://www.hhs.gov/coronavirus/index.html

Hue, B., Jinks, A., Spain, J., Bora, M., & Siew, S. (2019). Investment risk for long-term investors: risk measurement approaches: Considerations for pension funds and insurers. *British Actuarial Journal*, Published online by Cambridge University Press: 13 June. Available from internet: https://www.cambridge.org/core/journals/british-actuarial-journal/article/investment-risk-for-longterm-investors-risk-measurement-approaches-considerations-for-pension-funds-and-insurers/C328270AE15754B58CB7BC777CC46578

Hung, M. W., & Jan, Y. Ch. (2005). Sharpe Timing Ratio. *The Journal of Investing*, 14, (4), 75 – 79. Available from internet: https://www.pm-research.com/content/iijinvest/14/ 4/75; https://doi.org/10.3905/joi.2005.605285

Kabasinskas, A., Kopa, M., Sutiene, K., Lakstutiene, A., & Malakauskas, A. (2022). Performance evaluation of Lithuanian II pillar pension funds using rolling window technique. *Mathematical methods in economics 2022: 40th international conference*, 7 – 9 September 2020, Jihlava, Czech Republic: proceedings. Jihlava: College of polytechnics Jihlava, 154- 160.

Kabasinskas, A., Sutiene, K., Kopa, M. &Valakevicius, E. (2017). The risk and return profile of Lithuanian private pension funds. *Eeconomic research-Ekonomska istrazivanja*, 30, 1611–1630. https://doi.org/10.1080/1331677X.2017.1383169

Kabasinskas, A., Sutiene, K., Kopa, M., Luksys, K., & Bagdonas, K. (2020). Dominance-based decision rules for pension fund selection under different distributional assumptions. *Mathematics*, 8(5). https://doi.org/10.3390/math8050719

Kastelein, P. B., & Romp, W. E. (2020). Pension fund restoration policy in general equilibrium. *Macroeconomic Dynamics*, 24(7), 1785–1814. https://doi.org/10.1017/S1365100518001049

Kok, C., Mongelli, F. P., & Hobelsberger, K. (2022). A tale of three crises: synergies between ECB tasks. *ECB Occasional Paper*, (2022/305). https://doi.org/10.2139/ssrn.4219400

Kontosakos, V. E., Hwang, S., Kallinterakis, V., & Pantelous, A. A. (2024). Long-term dynamic asset allocation under asymmetric risk preferences. *European Journal of Operational Research*, 312(2), 765-782. https://doi.org/10.1016/ j.ejor.2023.07.038

Koop, G. (2017). Bayesian Methods for Empirical Macroeconomics with Big Data. *Review of Economic Analysis*, 9 (1), 33-56. https://doi.org/10.15353/rea.v9i1.1434

Kopa, M., Sutiene, K., Kabasinskas, K., Lakstutiene, A., & Malakauskas, A. (2022). A Dominance Tracking Index for Measuring Pension Fund Performance with Respect to the Benchmark. *Sustainability, 14,* 9532. https://doi.org/10.3390/su14159532

Lakstutiene, A., Kabasinskas, A., Kopa, M., Malakauskas, A., & Sutiene, K. (2024). The effect of short-term risks on Lithuanian pension fund performance. *46th EBES conference, January 10-12, 2024, Rome, Italy: proceedings*, 1.

Lan, Ch., Moneta, F., & Wermers, R. (2015). Mutual Fund Investment Horizon and Performance. Available from internet: https://www.cicfconf.org/sites/default/files/paper_786.pdf

Lestel, M. (2020). Performance Attribution from Bacon, February 5. Available from internet: https://cran.r-project.org/web/packages/PerformanceAnalytics/vignettes/PA-Bacon.pdf

Lieksnis, R. (2010). Evaluating the financial performance of Latvian and Estonian second-pillar pension funds. *Research in Economics and Business*, 2, 16–17.

Liu, J., Qiu, H., Zhao, X., & Zhu, Y. (2021). Modeling Optimal Pension Fund Asset Allocation in a Dynamic Capital Market. *Emerging Markets Finance and Trade*, 57(8), 2323-2330. Available from internet: https://doi.org/10.1080/1540496X.2019.1603521

Maiello, M. (2019). What Causes Stock Market Crashes, from Shanghai to Wall Street. *Chicago Booth Review.* Available from internet: https://www.chicagobooth.edu/review/what-causes-stock-market-crashes-shanghai-wall-street

Mantilla-Garcia, D., Martellini, L., Garcia-Huitron, M. E., & Martinez-Carrasco, M. A. (2024). Back to the funding ratio! Addressing the duration puzzle and retirement income risk of defined contribution pension plans. *Journal of Banking & Finance*, 159, 107061. Available from internet: https://doi.org/10.1016/j.jbankfin.2023.107061

Marshall, R. (2023). The Emerging Market crisis that never was. *LSEG.* Available from internet: https://www.lseg.com/en/insights/ftse-russell/emerging-market-crisis-never-was

Medaiskis, T. Gudaitis, T., & Meckovski, J. (2018). Optimal life-cycle investment strategy in Lithuanian second pension pillar. *International Journal of Economic Sciences*, VII (02). https://doi.org/10.20472/ES.2018.7.2.004

Medaiskis, T., & Gudaitis, T. (2017). Evaluation of second pillar pension funds supply and investment strategies in baltics. *Journal of Business Economics and Management*, 18 (6), 1174–1192. https://doi.org/10.3846/16111699.2017.1381145

Moller, D., & Pillay, D. (2014). Comparative Analysis of Student Investors Portfolio Management. https://doi.org/10.13140/2.1.3254.6241

Montrimas, A., Bruneckiene, J., & Giziene, V. (2023). Measuring Economic Resilience through Industrial Portfolio: the Cases of New EU Member States Since 2004. *Inzinerine Ekonomika-Engineering Economics*, 34(5), 593–611 https://doi.org/10.5755/j01.ee.34.5.35515

Nijman, T., & van Soest, A. (2018). Effective and Sustainable Private Pensions. *The Future of Ageing in Europe*, 79–106. https://doi.org/10.1007/978-981-13-1417-9_4

OECD (2011). OECD/ IOPS Good practices for Pension funds's risk management systems. Available from internet: https://www.oecd.org/finance/private-pensions/46864889.pdf

Pastor, L., Robert. F., & Stambaugh, R. F. (2012). On the Size of the Active Management Industry. *National Bureau of Economic Research*, Working Paper 15646, Available from internet: http://www.nber.org/papers/w15646; https://doi.org/10.3386/w15646;

Russia invaded Ukraine. (2023). Available from internet: https://war.ukraine.ua/

Salidjanova, N. (2016). Commission 1 China's Stock Market Meltdown Shakes the World, Again. *U.S.-China Economic and Security Review*. Available from internet: https://www.uscc.gov/sites/default/files/Research/Issue%20brief%20-%20China%27s%20Stocks%20Fall%20Again.pdf

Serletis, A., & Azad, N. F. (2020). Emerging Market Volatility Spillovers. *The American Economist*, 65 (1), 78-87. https://doi.org/10.1177/0569434518816445

Shi, Z., & Werker, B. J. M. (2012). Short-horizon regulation for long-term investors. *Journal of Banking & Finance*, 36(12), 3227-3238. https://doi.org/10.1016/j.jbankfin.2012.04.009

Steel, M. F. J. (2020), Model Averaging and Its Use in Economics. *Journal of Economic Literature*, 58(3), 644–719. https://doi.org/10.1257/jel.20191385

Strumskis, M., & Balkevicius, A. (2016). Pension fund participants and fund managing company shareholder relations in Lithuania second pillar pension funds. *Intellectual Economics*, 10 (1), 1-12. https://doi.org/10.1016/j.intele.2016.06.004

Taylor, J. W. (2022). Forecasting Value at Risk and expected shortfall using a model with a dynamic omega ratio. *Journal of Banking & Finance*, 140,106519, https://doi.org/10.1016/j.jbankfin.2022.106519

Taylor, M. (2024). What Is Total Risk: A Comprehensive Guide. Available from internet: https://www.shiftingshares.com/what-is-total-risk-a-comprehensive-guide-2/

van Bilsen, S., Laeven, R., & Nijman, T. (2020). Consumption and Portfolio Choice under Loss Aversion and Endogenous Updating of the Reference Level. *Management Science*, 66(9), 3927–3955.

Wang, L., Wang, Z., Zhao, S., & Tan, S. (2015). Stock market trend prediction using dynamical Bayesian factor graph. *Expert Systems with Applications*, 42(15), 6267-6275. *https://doi.org/10.1287/mnsc.2019.3393*

Xiao, Z., Hu, S., Zhang, Q., Tian, X., Chen, Y., Wang, J., & Chen, Z. (2019). Ensembles of change-point detectors: implications for real-time BMI applications, *Journal of computational neuroscience*, 46(1), 107–124. https://doi.org/10.1007/s10827-018-0694-8

Yumlu, M. S., Gurgen, F. S., Cemgil, A. T., & Okay, N. (2015). Bayesian changepoint and time-varying parameter learning in regime switching volatility models. *Digital Signal Processing*, 40, 198-212. https://doi.org/10.1016/ j.dsp.2015.02.001

Zhao, K., Valle, D., Popescu, S., Zhang, X., & Mallick B. (2013). Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. *Remote Sensing of Environment*, 132, 102-119. https://doi.org/10.1016/j.rse.2012.12.026

Zhao, K., Wulder, M. A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X., & Brown, M. (2019). Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. *Remote Sensing of Environment*, 232, 111181. https://doi.org/10.1016/j.rse.2019.04.034

Authors' Biographies

Aušrinė Lakštutienė Dr. is a professor at the School of Economics and Business, a member of the Sustainable Economics Research Group at Kaunas University of Technology. Research interests are in the areas of risk assessment, financial services development, financial institution management, and business financing sources rationing. ORCID iD 0000-0003-1130-2592.

Kristina Šutienė, Dr., is an Associate Professor at Faculty of Mathematics and Natural Sciences; Field of scientific research: mathematical modeling, artificial intelligence in finance and economics, risk assessment, sustainability. ORCID iD 0000-0001-5412-3194.

Audrius Kabasinskas is professor at department of Mathematical modeling, Faculty of Mathematics and Natural Sciences. His field of scientific research: mathematical finance, data analytics, risk measurement, mathematical modeling. ORCID iD 0000-0001-6863-5895.

Aidas Malakauskas is a PhD of economics and working in AB Swedbank as the Head of Financing Transformation Department. He is also a member of Sustainable Economics Research Group in School of Economics and Business at Kaunas University of Technology. Research interests are in the areas of credit risk, SMEs, access to finance, credit rationing, and machine learning. ORCID iD 0000-0001-6739-2481.

Miloš Kopa, Dr., is an Associate Professor at Charles University in Prague, Chair of Department of Probability and Mathematical Statistics in the Faculty of Mathematics and Physics, and Director of Financial Mathematics study; Field of scientific research: stochastic programming theory and applications, especially financial applications. ORCID iD 0000-0002-9438-4484.

The article has been reviewed.

Received in March 2024; accepted in May 2024.