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Systemic risk assessment of Lithuanian second-pillar pension funds through connectedness and spillover

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Abstract

Pension funds are an essential part of retirement planning, and their performance and risks play a significant role in ensuring financial stability for retirees. This study aims to analyse the connectedness and spillover effects in the Lithuanian second-pillar pension fund market. The findings of this study provide insight on the interdependence within the second-pillar pension funds market and with other financial markets, and contribute to a better understanding of the risk-return trade-off of pension funds, especially during high-volatility periods. Differently from other studies in this paper market regimes are identified using Hidden Markov Models (HMM). Interdependence (including multivariate and non-linear) and causality between pension funds are analysed in different market regimes. Finally, returns spillover in different regimes is estimated using VAR and VECM models. The results of this paper are expected to be useful for pension fund managers, participants, and pension system supervisors in making decisions about investment strategies and in practices of systemic risk management regulation.

Keywords: Systemic risk; Connectedness; Causality; Spillover; Lithuanian pension funds

1 Introduction

The second-pillar pension fund market has gained significant attention in recent years due to its potential to provide retirement benefits to individuals. However, the performance of this market is often impacted by spillover effects, which occur when events in one market sector affect the performance of other sectors. In the context of the second-pillar pension fund market, spillover effects can result from various factors such as world economic conditions, financial market stresses, and regulation changes.

Lithuania's pension system includes a mandatory first pillar (part of the social security system), a quasi-mandatory second pillar (defined contribution, life-cycle funds), and a completely voluntary third pillar, where individuals can save and accumulate additional funds for their retirement (see [48] for deeper insights on pension system in Lithuania). The performance of the second-pillar pension funds has been of interest to researchers, particularly regarding the risks-reward involved in the investments mainly focusing on

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non-systemic risk. This article contributes to measuring systemic risk, especially the effects of connectedness and spillover.

This study aims to analyse the interdependence and spillover effects in the Lithuanian second-pillar pension fund market. This research uses advanced econometric methods to identify market regimes, the presence of causality and spillover effects and assess their magnitude and direction. In the context of second-pillar pension funds, connectedness and spillover effects can have a significant impact on the risk and return of these funds. For instance, if there is high connectedness between different funds or markets, a shock in one market can quickly spread to other markets, leading to contagion effects. Similarly, if there are significant spillover effects between different funds or markets, the performance of one fund can affect the performance of other funds. This research sheds light on the relationship between the second-pillar pension fund market and other financial markets. This research adds to the increasing number of studies on the consequences of spillover effects on financial markets.

The remainder of the paper is organised as follows. Section 2 provides an overview of the scientific literature on Lithuanian pension funds and different approaches to systemic risk, contagion, and spillover. In the next Sect. 3 data and methodology are presented, and the choice of techniques and study scheme is also discussed. Finally, results on systemic risk and connectedness in the Lithuanian pension system are provided. The paper ends with conclusions.

2 Literature overview

Pension funds are an essential part of retirement planning, and their performance plays a significant role in ensuring financial stability for retirees. In Lithuania, the private pension fund industry has been growing rapidly since its inception in 2004, with more than 1.4 million participants and assets under management of EUR 5.6 billion as of 2022 [5]. The study [43] found that the funds have achieved attractive returns, despite the challenges posed by the global financial crisis and the European debt crisis. On the contrary, the pension fund industry in other countries, such as Slovakia, has faced challenges due to regulatory changes. A study that analysed the impact of regulatory changes on the performance of Slovakian pension funds found that the changes had a negative impact on their performance [64]. The study suggests that the changes had the unintended consequence of discouraging participation in pension funds, which had a negative impact on their asset allocation and investment performance [64].

The impact of financial crises on pension fund performance has been examined in several studies. For example, a study on the withdrawal from mandatory pension funds in Eastern and Central Europe as a result of the financial and fiscal crisis found that the crisis had a negative impact on pension fund performance and that the withdrawal was a temporary solution to address short-term fiscal pressures [61]. Similarly, a study on the resilience of the US corporate bond market during financial crises [8] found that pension funds with greater exposure to corporate bonds had lower returns during crises. Moreover, mathematical modelling shows that riskier funds may recover faster after a crisis compared to more conservative funds [41].

To mitigate the risks associated with pension fund investments, various methods have been employed, such as stochastic programming models. For example, a study on personal savings accrual in Lithuania used a multistage risk-averse stochastic programming model to optimise investment decisions [42]. The study found that the model helped reduce the risk associated with the accrual of personal savings and increased the expected rate of return. The behaviour of pension fund participants is also an important factor in pension fund performance. A study of the behaviour of participants in the second pension pillar in Lithuania found that participants tended to invest more conservatively, despite the potentially higher returns of riskier investments [47, 61]. The later study suggests that the risk aversion of participants may be driven by the lack of financial literacy and the perceived risks associated with investing. This may have contributed to lower returns on pension funds in Lithuania compared to other countries. However, participants were not always aware of the risks involved in the investments they selected. Furthermore, the study [66] on pension systems as risk management in Baltic states emphasised the importance of diversification and risk management in pension fund investment strategies to mitigate the impact of financial crises and the effects of contagion.

The connectedness and systemic risks associated with pension fund investments have been examined using various approaches, such as dominance-based decision rules. For example, a study on dominance-based decision rules for pension fund selection under different distributional assumptions found that these rules can help identify funds with superior performance relative to their benchmarks [48]. Another study on the use of outcome-based benchmarks in pension fund investment found that such benchmarks can incentivise long-term investment and reduce the impact of short-term market fluctuations on pension fund performance [68].

Overall, the performance of pension funds in Lithuania has been relatively strong, with diversified investment strategies that have reduced exposure to systemic risks. However, the impact of regulatory changes, financial crises, and the behaviour of participants should not be overlooked. The use of stochastic programming models, dominance-based decision rules, and outcome-based benchmarks can help mitigate the risks associated with pension fund investments and improve their performance.

Few articles focus on pension systems in the Baltic States, including Lithuania, Estonia, and Latvia [2, 12, 43, 44, 60, 61, 77]. Some articles also compare the pension systems of these countries with other European countries such as Sweden [58, 59], Slovakia [43, 64], Turkey [72] and Croatia [25]. Some articles also examine the impact of the COVID-19 crisis on pension fund management around the word [8, 17, 33, 38, 53, 54]. Some papers [4, 10] primarily discuss the impact of financial and fiscal crises on mandatory pension systems, rather than private pension funds. The relations between Mexican pension funds were analysed in [17]. They introduced financial-connectedness indicators for daily returns, finding a high degree of linkage and spillovers. However, they used VAR models, which are applicable only to stationery data sets. The articles [8, 33, 38, 53, 54, 72] focus on specific financial crises or the impact of the COVID-19 pandemic on pension funds. Although these articles provide valuable information, they could be useful in analysing the results of private pension funds in Lithuania. The behaviour of the participants in the second pillar pension fund participants in Baltic [2, 61] and other countries [65] is analysed in some articles. The herding behaviour among pension fund managers was also analysed in the last one.

Spillover effects refer to the transmission of shocks, returns, or other financial market conditions from one market to another [79]. In the context of international financial markets, spillover effects occur when financial conditions in one country or financial market affect the performance of other countries or financial markets. This can happen through various channels, such as trade linkages, capital flows, and market interdependence. Studies on spillover effects in international financial markets have found evidence of interdependence between different financial markets, such as stock markets, bond markets, and currency markets. The 2008 financial crisis is another example of how spillover effects can occur in international financial markets. The crisis, which originated in the US housing market, spread globally and affected the performance of stock markets worldwide. This demonstrates the potential for events in one country or financial market to have significant spillover effects on other countries or financial markets.

One of the first studies on spillover effects between pension funds and financial markets was conducted by Ferson and Schadt [34], who examined the relationship between pension fund asset allocations and stock market returns. They found that changes in pension fund allocations to stocks had a positive impact on stock market returns, suggesting that pension funds have a spillover effect on the stock market.

In general, the literature suggests that pension funds have a spillover effect on financial markets, particularly in the case of equity markets. However, the extent and nature of these spillover effects can vary depending on a variety of factors, such as the size and investment strategy of the pension fund, the asset class in question, and the broader economic and financial environment.

Many articles examine spillover and connectedness among various financial markets and assets. While they share a common focus on the propagation of shocks and the transmission of information among markets, their findings reveal notable differences. Some articles focus on the dynamics of spillover effects during specific events, such as the European sovereign debt crisis or the COVID-19 pandemic [1, 51], while others analyse the general structure of interdependence among global markets [9]. The spillover effects among various financial markets across different quantiles were studied in [79]. It focuses on understanding the changes in spillovers during different market conditions and identifies the sources and directions of spillovers. The spillover effects of the European sovereign debt crisis on financial markets were examined in [1]. They found that the bond crisis had a significant impact on the financial markets and the effects were persistent over time. A better understanding of the drivers of interdependence and the implications of these interdependencies for risk management was studied in [9]. The development of new economic measures to analyse connectedness and systemic risk in the finance and insurance sectors was presented in [11]. While [20] investigates asymmetry in the distribution of returns and volatility between Australian equity and bond markets. Dynamic spillover effects in various markets (commodity, cryptocurrency) were analysed in [18, 45, 49, 52, 81]. They emphasise that there are significant spillovers between financial markets and that the spillovers change over time. The paper [75] focuses on the long-term spillover effects between the stock markets and cryptocurrencies. It studies the impact of stock market returns and volatility on cryptocurrency returns and volatility, and vice versa. On the other hand, the paper [49] is focused solely on short-term spillover effects between different cryptocurrencies only. In addition, the articles use different methods to study spillovers, such as network analysis or time-varying volatility spillovers [11, 26, 49, 52, 62, 78, 79, 81]. Similarly, [78] examined the spillover of risk from the Chinese and US stock markets during high volatility periods. It finds that there are significant spillovers from both markets and that the spillovers are greater during high-volatility periods. Recently, [62] analysed the frequency spillovers between green bonds, global factors, and stock markets before and during the COVID-19 crisis. It turned out that spillovers change during the crisis and that the green bonds market is affected by both global factors and own-return shocks. Moreover, they found significant nonlinear relationships between markets. Hence, a complex network of interdependencies [80] were used to analyse the extreme risk spillovers between traditional financial and FinTech institutions. For example, papers [1, 75, 80] focus on spillover effects during high-volatility periods, which could provide insight into how markets are impacted during crises. Papers [11, 26, 49, 52, 62, 78, 79, 81] examine different methods for studying spillovers, such as network analysis or time-varying volatility spillovers, which could help identify which methods are most effective for analysing financial interdependence. Finally, papers [9, 18, 20, 45, 62, 81] examine different types of markets and assets, which could be useful for diversifying pension fund portfolios during crisis periods.

Some of the articles may use related techniques or methods for analysing financial interdependence and spillover effects. For example, [11, 79] uses a systemic risk measure based on variance decomposition, which is related to the concept of stochastic dominance. The paper [75] uses vector autoregressive models to study the effects of spillover between different financial assets. There are several studies that provide an overview of financial contagion, which refers to the transmission of financial crises from one country to another, and investigates the channels through which financial contagion occurs [3, 21, 37]. These studies provide evidence that financial contagion is an important consideration during financial crises, as changes in one country can quickly spread to other countries.

Barunik and Krehlik [6] analyse the spillover effects of financial volatility on economic activity. They examine how changes in financial volatility in one market affect economic activity in other markets. Diebold and Yilmaz [23, 24], on the other hand, focus on spillovers in the volatility of financial markets. They study how changes in volatility in one market can impact volatility in other markets, both directly and indirectly. Their most recent work [22] focuses on dynamic spillover in high-dimensional systems. The paper [63] uses a more comprehensive approach that combines network analysis with econometric techniques to measure spillover effects between different cryptocurrencies. In contrast, [56] uses a more narrow approach, relying on Vector Autoregression (VAR) and Vector Autoregression-Structural VAR (VAR-SVAR) models to assess the spillover risk in the cryptocurrency market. In general, both studies contribute to understanding the spillover effects on the cryptocurrency market, with [63] offering a more in-depth analysis.

There are various methods to analyse spillover and connectedness in financial markets [50]. Some of the methods used include:

– Econometric measures. The articles use econometric measures such as vector autoregression models (VAR) [46, 55], vector error correction models (VECM) [28, 74], dynamic conditional correlation (DCC) models [19, 29], and generalised autoregressive conditional heteroscedasticity models (GARCH) [14, 27] to analyse the interdependence and spillover effects between financial markets. The VAR model is a multivariate time series model that aims to capture the interdependence between multiple variables over time. It is based on the assumption that past values of a set of variables help predict future values. In the context of spillover and connectedness in pension funds, the VAR model can be used to analyze the relationships between different types of investments and their performance. The VECM model is an extension of the VAR model that allows for the presence of cointegration between variables. This model is useful in situations where there is a long-run relationship between variables and can provide insight into how changes in one variable influence changes in other variables over time. In the context of pension funds, the VECM model can be used to understand how spillovers from one investment class affect other investment classes and how these spillovers change over time. The DCC model is a multivariate model that captures the time-varying relationships between variables. Unlike the VAR and VECM models, the DCC model does not assume a constant relationship between variables, but rather one that changes over time. This model is particularly useful for capturing the dynamics of spillover and connectedness in pension funds and can provide insight into the changing relationships between different investment classes and their volatility. Unfortunately, BEKK-GARCH seems to be the incorrect model, according to [57], for the analysis of spillover. The diagonal BEKK-GARCH could be useful for the analysis of spillover between returns. However, it does not seem to allow volatility spillovers [30]. Some studies have used DCC-GARCH to analyse spillover. However, this model does not allow volatility spillovers by design. In addition, there are also other problems related to this approach [57]. GO-GARCH as a multivariate GARCH model is quite suitable for spillover analysis [7, 70]. Nevertheless, in this paper, only VAR and VECM models are considered and the reasons are explained in the Methodology Sect. 3.

- Complex network perspective. One of the articles uses a complex network perspective to examine extreme risk spillovers between traditional financial and FinTech institutions [80]. This method allows for a visual representation of the interconnectedness between financial institutions and the flow of risk between them.
- Asymmetry analysis. Several articles use asymmetry analysis [71] to examine return asymmetry and volatility spillovers between financial markets. This approach helps identify the direction and magnitude of spillovers between financial markets and determine whether the spillovers are asymmetric or not. Asymmetry analysis is a method used to analyse the asymmetrical behaviour of variables, such as returns and volatility. In the context of spillover and connectedness in pension funds, asymmetry analysis can be used to understand differences in the way that returns and volatility of different investment classes affect each other. For example, it can help determine whether a shock to one investment class has a different effect on the returns or volatility of another investment class compared to the reverse.
- Time-varying volatility spillovers. Some papers use a method to analyse time-varying volatility [52] spillovers between crude oil or other markets. This method allows for a more accurate and dynamic analysis of volatility spillovers, taking into account the changing nature of financial markets over time.
- Causality analysis. Many articles use causality analysis, e.g. [35], to examine the relationship between institutional investment, equity volume, and volatility spillover. This method helps determine the causalities and asymmetries in spillovers between financial markets. Causality analysis is a method used to determine the cause-and-effect relationships between variables. In the context of spillover and connectedness in pension funds, causality analysis can be used to determine whether changes in one investment class drive changes in another investment class, or whether changes are driven by external factors. This information can provide insight into how

investment classes are interconnected and how changes in one investment class can affect others.

Econometric measures and causality analysis could be used to examine the spillover effects from other financial markets to pension funds, helping investors and decision-makers to assess the risk of their investments. The complex network perspective could also be used to visualise the interconnectedness between pension funds and other financial institutions and to identify the flow of risk between them.

In general, the methods used in these articles provide a comprehensive analysis of spillover and connectedness in financial markets, helping to shed light on the interdependence between financial markets and the potential impacts of spillovers during high-volatility periods. For example, a pension fund that invests heavily in the stock market could be affected by spillovers from the bond market or other financial markets, which could result in future loss of value.

3 Data and methodology

In this section, data and methodology are described how to reveal connectedness in the Lithuanian IInd pillar pension fund market. The period of interest is from January 2019 (the introduction of life-cycle pension funds) to September 2022. At the end of the period analysed, there were 48 life-cycle pension funds managed by 6 companies in Lithuania. However, the pension fund manager Goindex joined the system in mid-2022 only; therefore, it is excluded from further analyses. The rest of the pension funds have a long enough history and can be used in statistical analyses. According to the pension system law [69] for every participant of the II pillar of the pension system, there should be a proposed life cycle pension fund, which corresponds to his age. Currently, there are 7 pension fund groups (corresponding to the age of the participant) for accumulation and one group for asset preservation pension funds. The name of the fund (in tables and figures) is led by numbers indicating the year of birth of the participant, e.g. notation Allianz_54.60 or Allianz 54–60 indicates that the fund is managed by Allianz and the participant is born between (19)54 and (19)60. While symbol T indicates preservation fund. Depending on the age of the participant, pension funds must follow a predefined strategy (glide path) [48]. However, pension funds are allowed to deviate by ± 10 % from the typical investment strategy (see Table 1). Furthermore, every PF must follow a benchmark index (see [48] how well they were doing this), which is also defined in the investment strategy.

As we can see in Table 1, the largest pension fund at the end of September 2022 was Swedbank 68–74 which invests nearly 80% of assets in stocks or funds. Generally speaking, during the 3 years analysed, allocations in stocks have decreased for all PFs. The largest pension fund manager (by asset value and number of participants) was also Swedbank. More details and statistical insights on PFs in Lithuania can be found in paper [40].

The second data set is taken to analyse conditions of financial markets (is separated from Lithuanian IInd pillar pension funds). This data set contains SnP500, Stoxx600, N100, N225, MSCI world, EURO bonds, and FVX observations from January 2007 until September 2022. In Table 2 details are given on the indices used.

Two indices (in Table 2) are from Europe, one from the United States, one from Japan, one is a global index, one is EURO bond index and one US Treasury bond index. They cover the most important financial markets where Lithuanian IInd pillar pension funds invest and allow to catch shocks (if any) in the markets. Some of them are used as benchmarks (see [48]) by pension fund managers.

Table 1 Size of PF in Jan 2019 and Sep 2022, and investment strategy into stocks

Fund	January 2019			September 2022			Manager	Market share (%)
	Number of participants	Net assets, mln EUR	Share of stocks*	Number of participants	Net assets, mln EUR	Share of stocks**		
Allianz_54.60	612	1.91	31	12,438	54.49	15	Allianz Lietuva gyvybės draudimas UAB	14.41
Allianz_61.67	1275	3.65	53	38,793	168.25	45		
Allianz_68.74	1382	3.22	93	40,347	177.87	80		
Allianz_75.81	1408	2.86	100	40,494	160.22	90		
Allianz_82.88	1546	1.94	100	48,274	126.62	90		
Allianz_89.95	1160	0.79	100	34,038	70.00	90		
Allianz_96.02	611	0.14	100	20,023	18.84	90		
Allianz_T	148	0.47	10	4628	13.52	10		
INVL_54.60	7200	27.93	25	4131	21.19	10	UAB "INVL Asset Management"	13.98
INVL_61.67	17,798	72.44	66	17,910	101.28	38		
INVL_68.74	21,688	95.67	100	23,492	157.88	74		
INVL_75.81	23,944	101.24	100	28,070	186.80	97		
INVL_82.88	36,344	83.90	100	44,285	176.77	97		
INVL_89.95	24,992	32.40	100	36,581	94.98	97		
INVL_96.02	4946	2.75	100	18,815	19.66	97		
INVL_T	372	1.27	27	1608	7.30	17		
Luminor_54.60	199	0.71	35	5363	22.54	10	Luminor investicijų valdymas UAB	7.64
Luminor_61.67	293	1.11	70	17,129	78.69	45		
Luminor_68.74	351	1.04	100	18,812	95.80	80		
Luminor_75.81	353	1.04	100	20,269	95.14	90		
Luminor_82.88	485	0.89	100	26,046	77.90	90		
Luminor_89.95	441	0.37	100	18,486	36.44	90		
Luminor_96.02	229	0.08	100	13,479	7.21	90		
Luminor_T	38	0.17	20	1847	5.20	10		
SEB_54.60	639	2.02	32	13,978	68.55	18.5	UAB "SEB investicijų valdymas"	25.95
SEB_61.67	1567	4.78	69	47,044	251.42	44.4		
SEB_68.74	1694	5.10	100	53,507	323.68	78		
SEB_75.81	1847	5.00	100	62,549	353.32	98		
SEB_82.88	2451	3.97	100	73,060	266.86	98		
SEB_89.95	2156	1.92	100	45,505	110.80	98		
SEB_96.02	817	0.45	100	20,744	23.01	98		
SEB_T	52	0.30	25	5810	24.38	15		
Swedbank_54.60	1281	9.31	35	21,827	97.52	15	UAB "Swedbank investicijų valdymas"	38.02
Swedbank_61.67	7474	4.23	70	84,743	373.20	45		
Swedbank_68.74	9487	23.48	100	95,662	472.99	80		
Swedbank_75.81	9281	28.75	100	97,802	458.23	97		
Swedbank_82.88	10,715	25.08	100	110,147	357.80	97		
Swedbank_89.95	13,185	17.93	100	93,286	236.73	97		
Swedbank_96.02	8748	9.01	100	45,407	55.21	97		
Swedbank_T	127	38.87	25	5190	31.56	15		

* up to %.
** may deviate by 10%.
Note. See Table 8 for full original names of funds and managing companies.

The remainder of this section is structured as follows. First, the methodology of how potential market regimes are identified using HMM models with external data (stock indices from around the world and bond indices) is provided. Secondly, correlational analysis (including multivariate and non-linear) between PFs is discussed. Third, the idea of how to check what information is useful in the prediction of PF returns using Granger causality is discussed. Finally, a scheme of how returns spillover in different regimes can be estimated using VECM and VAR (for comparison purposes) models is provided.

Table 2 Description of financial indices used

Index	Full name	Start value	End value	Mean return	Std. dev.	Comment
SnP500	S&P 500	1418.3	3585.62	0.00040	0.0124	a stock market index that tracks the stock performance of 500 large companies listed on U.S. stock exchanges
Stoxx600	Stoxx600	365.26	387.85	0.00020	0.0120	a stock market index that tracks the performance of 600 large, mid-sized, and small companies in 17 European countries
N100	Euronext	962.84	1113.98	0.00023	0.0127	stock market index that tracks the performance of the 100 largest and most liquid companies listed on Euronext Paris
N225	Nikkei 225	17,225.83	25,937.21	0.00007	0.0151	a stock market index that represents the performance of the top 225 companies listed on the Tokyo Stock Exchange (TSE)
MSCI_world	MSCI World Daily Net Total Return	114.885	267.071	0.00036	0.0102	a stock market index that represents the performance of large and mid-cap stocks across 23 developed countries, including the United States, Canada, Japan, and countries in Europe and the Asia-Pacific region
EURO_bonds	Bloomberg Series-E Euro Govt 1–5 Yr Bond	134.5671	175.3489	0.00003	0.0011	a bond index that represents the performance of short-term fixed-income securities issued by eurozone governments, with a maturity of between 1 and 5 years
FVX	CBOE Treasury Yield Index for the 5-Year Treasury note	4.701	4.041	0.00054	0.0393	5-Year Treasury Constant Maturity Rate (Futures contract traded on the CBOT), which is a yield curve benchmark used in the United States to measure the interest rate on US Treasury securities with a maturity of 5 years

Note. Mean and Std. Dev. are provided for daily log-returns.

3.1 Market regime identification

As mentioned in the Introduction, most of the papers that analyse connectedness and spillover do not perform market regime detection, they mainly assume that a true market crisis (e.g., COVID-19) started on a particular day without checking if such regime switching was observed or not.

More precisely, it is said that the asset A at time t is in state $s_t \in S$ if the probability $P(A_t = s_t)$ of being in state s exceeds 1/2. Moreover, in the case of Markov chain, it is assumed that this probability depends only on the state at time $t-1$, i.e.,

$$P(A_t = s_t | A_{t-1} = s_{t-1}, A_{t-2} = s_{t-2}, \dots, A_1 = s_1) = P(A_t = s_t | A_{t-1} = s_{t-1}). \qquad (1)$$

Depending on the set of possible states S this can be rewritten as

$$P(A_t = s_t | A_{t-1} = s_{t-1}) = P(A_t = j | A_{t-1} = i) = p_{ij}, \qquad (2)$$

for $i, j \in S$ and $t = 1, 2, \dots, T$. Equation (2) defines the Markov chain transition matrix.

In this paper it is assumed that there are only two states $S = \{\text{“no-stress”}, \text{“stress”}\}$ on the corresponding market and that they are observed indirectly. Such states are called Hidden Markov states. For example, in this study, only daily returns of pension funds are observed, whereas unobservable states of the market are hidden from the observer. Transition probabilities of hidden states can be estimated using many techniques; however, in this paper the methodology provided in paper [76] was used. Two mentioned states are detected for all stock indices (SP500, Stoxx600, N100, N225, MSCI world) and bonds (EURO bond and FVX). The paper [76] proposed two interesting techniques for regime detection. The first technique (denoted as $m = 1$) uses only the index history to identify hidden states. The second one (denoted $m = 2$) detects regimes using not only their own history, but also observations of other indices as regressors. Both approaches later can be aggregated (using any decision-making technique) into a single set of regime levels, e.g.,

$$L_t^i = \sum_{m=1}^{M} w_m s_t^{i,m}, \quad \forall i = 1, \dots, N, \ \forall t = 1, \dots, T \tag{3}$$

here M shows the number of state detection techniques used, w_m is the importance of a technique (in this paper equal to 1/2), N is the number of market indices analysed and T is the time horizon.

This information on separate levels from all the indices is then combined into four regimes. More precisely, levels of stock indices are aggregated to regime levels of stocks L_t^{Stocks} and levels of bond indices are aggregated to regime levels of bonds L_t^{Bonds} correspondingly

$$L_t^{\text{Stocks}} = \sum_{n=1}^{N_s} w_n^s L_t^n,$$

$$L_t^{\text{Bonds}} = \sum_{n=1}^{N_b} w_n^b L_t^n,$$

where N_s and N_b are the corresponding numbers of stock and bond indices analysed, w_n^s and w_n^b are the weights (importance among stocks or bonds) of each index. To represent the situation in the global market, the weights are set to $w^s = 1/N_s$ and $w^b = 1/N_b$ correspondingly. However, if a more regional situation is needed, the weights should be adjusted. It must be noted that both $L_t^{\text{Stocks}} \in [1, 2]$ and $L_t^{\text{Bonds}} \in [1, 2]$ are real numbers, and it is not straightforward to decide which state (shock, no-shock) they represent. To solve this issue in this paper, the empirical threshold is set for stock indices at 1.3 and 1.5 for bond indices. If the regime level is equal to or exceeds a threshold, then it is assumed that there is a shock in the corresponding market. In such a way, two sets of market states S_t^{Stocks} and S_t^{Bonds} ($\forall t = 1, \dots, T$) are estimated.

Finally, they are combined, and the market regime is identified. In particular, Regime 1 describes the situation when no shocks are detected (state 1 is observed in most of the indices), Regime 2 describes the situation when the shock is observed in most of the stock indices, Regime 3 describes the situation when the shock is observed in bond indices and treasury bills, and Regime 4 describes the situation when the shock state is observed in stock and in bond indices simultaneously. Mathematically this can be represented as follows

$$R_t = \begin{cases} \text{Regime 1}, & \text{if } (S_t^{\text{Stocks}} = \text{"no-stress"}) \ \& \ (S_t^{\text{Bonds}} = \text{"no-stress"}), \\ \text{Regime 2}, & \text{if } (S^{\text{Stocks}} = \text{"stress"}) \ \& \ (S^{\text{Bonds}} = \text{"no-stress"}), \\ \text{Regime 3}, & \text{if } (S^{\text{Stocks}} = \text{"no-stress"}) \ \& \ (S^{\text{Bonds}} = \text{"stress"}), \\ \text{Regime 4}, & \text{if } (S^{\text{Stocks}} = \text{"stress"}) \ \& \ (S^{\text{Bonds}} = \text{"stress"}). \end{cases} \tag{4}$$

At the moment $t = 1, \dots, T$ the market can only be in one of the above regimes R_t. The sequence of regimes $R = R_1, R_2, \dots, R_T$ could also be a Markov chain with 4 states if it follows the Markovianity property (2).

In this paper, the HMM was run for the period 2007–2022 to identify four regimes from market indices that are directly not related to the pension system in Lithuania.

3.2 Correlation and dependencies

Pearson correlation coefficient is used to describe the linear correlation between pension funds, however, depending on the regime detected in the previous section, these correlations may be different. Moreover, it is a well-known fact that during turbulence periods dependencies between financial data may deviate from linear. Therefore, the non-linear correlation coefficient is used [67].

It is important to understand not only how pension funds are correlated to each other, but also how they correlate to groups of other financial data sets. For this purpose, multivariate or interclass [16] correlation is used (see [73] for technical details).

3.3 Causality

Establishing causality between financial data sets is a complex and challenging task, as there may be multiple factors that affect the observed changes in the data. Here are some methods that are used to show causality between financial data sets:

- Granger [35, 71] causality test;
- regression analysis [32, 39];
- event studies [15, 31];
- Structural Equation Modelling (SEM) [13, 36].

In this paper, only the Granger test is used. This test is widely used in economics and finance to establish causality between two time series. It determines whether the past values of one time series can help predict the future values of another time series. The test involves estimating two regression models, one with the past values of the potential cause and one without. To test for Granger causality from Asset 1 to Asset 2, the following regression equation is assumed:

$$X_t^2 = \alpha + \beta_1 X_{t-1}^1 + \beta_2 X_{t-1}^2 + \varepsilon_t, \tag{5}$$

where X_t^1 and X_t^2 are returns of Asset 1 and Asset 2 correspondingly. If β_1 is statistically significant, it suggests a return causality from Asset 1 to Asset 2. In other words, if the inclusion of past values improves the predictability of the dependent variable, then causality can be established. It is important to note that establishing causality in finance is challenging due to the presence of confounding variables, stationarity of the data, and other factors that can influence results. Therefore, it is important to carefully design the analysis and to take into account any potential alternative explanations for the observed relationships.

Indeed, stationarity (according to ADF and KPSS tests) was not observed in the data analysed (entire period case). However, some time series become stationary once the data are separated according to the detected HMM regimes. This suggests that the results of the Granger causality are more reliable for regime data, while the conclusion on the entire period should be treated with caution.

3.4 Spillover

Total spillover between two assets i and j in very simple way can be defined as

$$\text{Spillover}_{i\to j} = \frac{1}{T}\sum_{t=1}^{T}\frac{\operatorname{Cov}(\varepsilon_{it},\varepsilon_{jt})^2}{\sum_{k=1}^{N}\operatorname{Var}(\varepsilon_{kt})^2}, \tag{6}$$

where T is the total number of observations (time periods), N is the total number of assets being considered, ε_{it} is the residual of variable i at time t, $\operatorname{Cov}(\varepsilon_{it},\varepsilon_{jt})$ is the covariance between the residuals of variable i and variable j at time t, the denominator term $\sum_{k=1}^{N}\operatorname{Var}(\varepsilon_{kt})^2$ represents the sum of the squared variances of residuals for all variables k at time t. There are a few interesting approaches to spillover analysis, which differ in the way ε_{it} are calculated. The two most simple are definitely VAR (Vector Autoregression) and VECM (Vector Error Correction Model). Their use is widely analysed in Sect. 2. In a VAR model [23, 24], the variables are assumed to be stationary, which means that their means and variances remain constant over time. More precisely, the general form of a VAR(p) model for N variables is as follows

$$Y_t = c + A_1Y_{t-1} + A_2Y_{t-2} + \cdots + A_pY_{t-p} + \varepsilon_t,$$

where Y_t is an $N \times 1$ vector of variables at time t, c is a constant term, A_i are coefficient matrices for lag i, p is the number of lags, ε_t is an $N \times 1$ vector of error terms. VAR models allow for the analysis of the dynamic interactions between multiple time series variables. They capture the short-term and long-term relationships between the variables without imposing any constraints on the direction of causality. Spillover effects are analysed by estimating impulse response functions. These functions show the dynamic response of each variable in the system to a one-time shock in one of the variables, keeping all other variables constant. When examining the impulse response functions for each variable, one can identify the magnitude, direction, and timing of the spillover effects between the variables. In contrast, VECM [74] models are designed to analyse non-stationary time series data that may exhibit cointegration. The general form of a VECM for N cointegrated variables is as follows

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1}\Gamma_i\Delta Y_{t-i} + \varepsilon_t,$$

where ΔY_t is an $N \times 1$ vector of first differences of variables at time t, Π is the cointegration matrix, Γ_i are coefficient matrices for lagged first differences, p is the number of lags, ε_t is an $N \times 1$ vector of error terms. Cointegration occurs when two or more non-stationary time series are linearly related in such a way that they move together over the long run, even though they may differ in their short-term behaviour. VECM models capture long-term equilibrium relationships between variables, as well as short-term dynamic adjustments that occur when the variables deviate from their equilibrium values. VECM models restrict the direction of causality, requiring that long-term equilibrium relationships be driven by one or more of the variables in the system. In this case, spillover effects can be analysed by examining the short-term and long-term relationships between the variables. Cointegration between the variables implies a long-term equilibrium relationship that determines the direction and magnitude of spillover effects. Granger causality tests can be used to identify the direction of causality between variables in the system, and impulse response functions can be estimated to analyse the dynamic response of each variable to shocks in the system.

Volatility in pension funds is difficult to analyse (because of data specifics) compared to stocks or crypto-currencies, therefore, in this paper, only VAR and VECM models (up to lag 10) are considered, as they are simple and provide useful tools to analyse spillover effects and understand the interdependence between variables in the pension fund market.

Together with total spillover, partial spillovers are analysed. They are known as "net", "from" and "to" spillovers.

Net spillover focusses on the net effect of spillover from multiple sources to a target asset or market. It takes into account both positive ('from') and negative ('to') influences. Net spillover can be a useful indicator of the overall impact of various shocks on a specific asset. Net spillover can be calculated as the difference between the "from" (total positive) spillover and the "to" (total negative) spillover to the target asset. Mathematically,

$$\text{Net Spillover} = \text{“from”} - \text{“to”},$$

where positive and negative spillover can be calculated using appropriate metrics (see [6] for calculation details).

To quantify the total impact of shocks or changes in all assets on the entire market, overall spillover can be computed. It considers the collective transmission of information, volatility, or other factors that can lead to simultaneous movements in different assets. A common way to measure overall spillover is by computing the Eigenvalue-based Spillover Index. This index captures the proportion of total variance in all assets that is due to spillover effects. Mathematically, the Eigenvalue-based Spillover Index can be defined as

$$\text{Overall Spillover} = \frac{1}{N}\sum_{i=1}^{N}\lambda_i,$$

where N is the total number of assets, λ_i represents the i-th eigenvalue of the asset returns covariance matrix. The higher the overall spillover value, the greater the influence of spillover effects in the market, indicating greater interconnectivity and potential contagion.

The general scheme of the research is provided in Fig. 1.

As can be seen in the figure above, there are five data samples: entire period data and data from four regimes. All of them contain returns of funds and indices. However, for some analytical and comparison purposes, the market indices are sometimes separated.

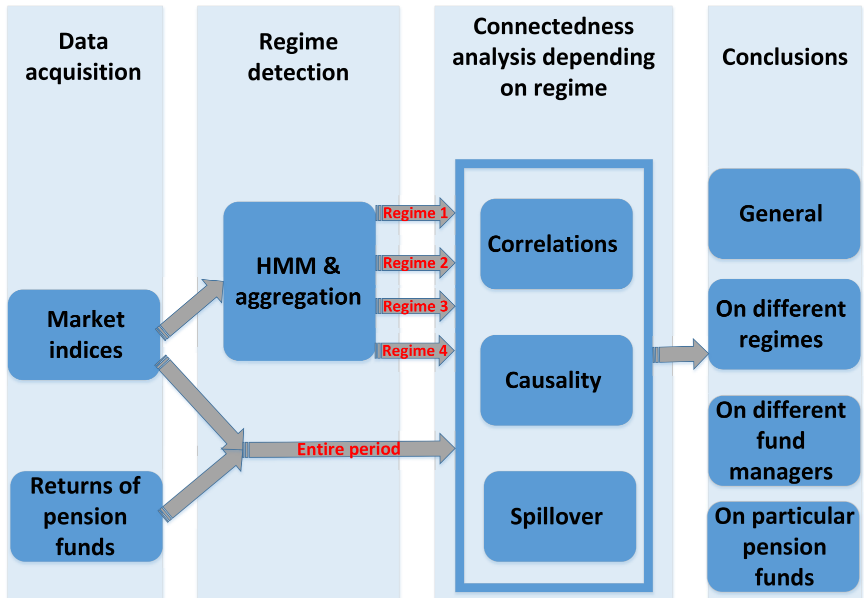

Figure 1 The general scheme of the research

Furthermore, Regime 3 is too short for most analytical methods, therefore it is excluded from causality and spillover.

4 Results

This section begins with the detection of regimes in financial markets. Unlike other papers, where the crisis is not identified but taken as it is, in this research, shocks are identified using various financial indices, the HMM technique, and multi-criteria decision-making techniques. First, the HMM regime detection technique [76] is used to identify hidden states in each financial index (see Table 2 for a complete list) separately. Later, hidden regimes in each index are detected using all financial indices as exogenous factors. In Fig. 2 the states detected using both approaches are shown.

According to the first approach, hidden states are implicit in returns of the financial index without exogenous information (see Fig. 2 left). The second approach assumes that hidden states depend on the returns of the indices of other markets (see Fig. 2 right). Furthermore, learning from the own history identifies a more random appearance of state 2, compared to identification using information from the entire market.

Later, the states of each financial index in Fig. 2 are aggregated (equally weighted averaging) into a single data set. The results of this aggregation are provided in Fig. 3.

Level 1 of the regime (from Fig. 3) defines the situation when no shock is detected for a particular index. The intermediate level describes the situation where the shock is detected by one of the techniques, and level 2 corresponds to the situation where the shock is detected using both techniques. The aggregation method could be adjusted if a more sophisticated decision-making method is necessary to use.

In Fig. 4 aggregate levels of the regimes for the stock and bond indices are provided separately.

The weights during aggregation are the same for all the indices; however, this can be adjusted if a more regional or global result is needed. Additionally, in Fig. 4 threshold

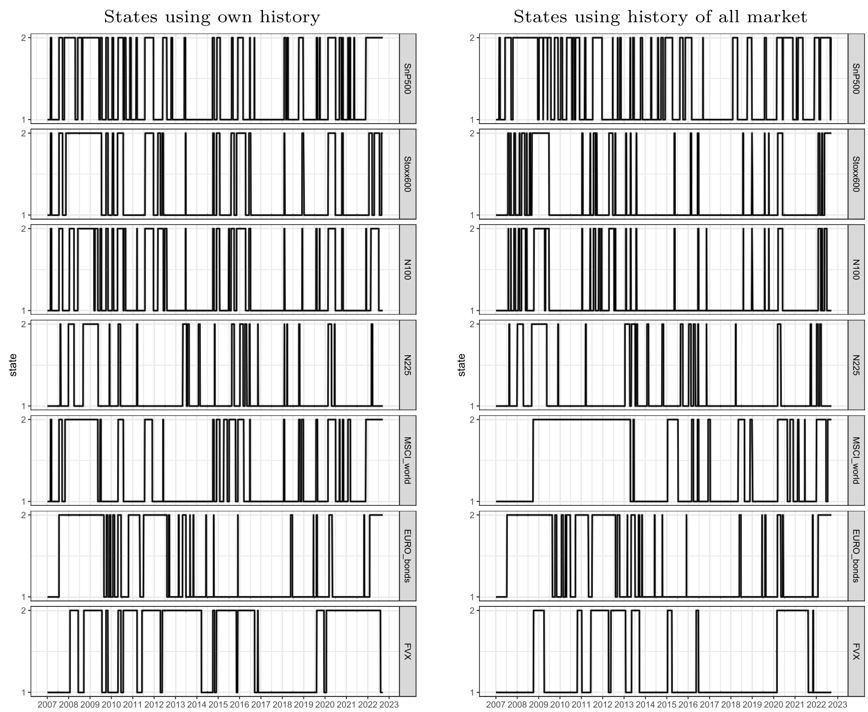

Figure 2 Detected states of financial market indices

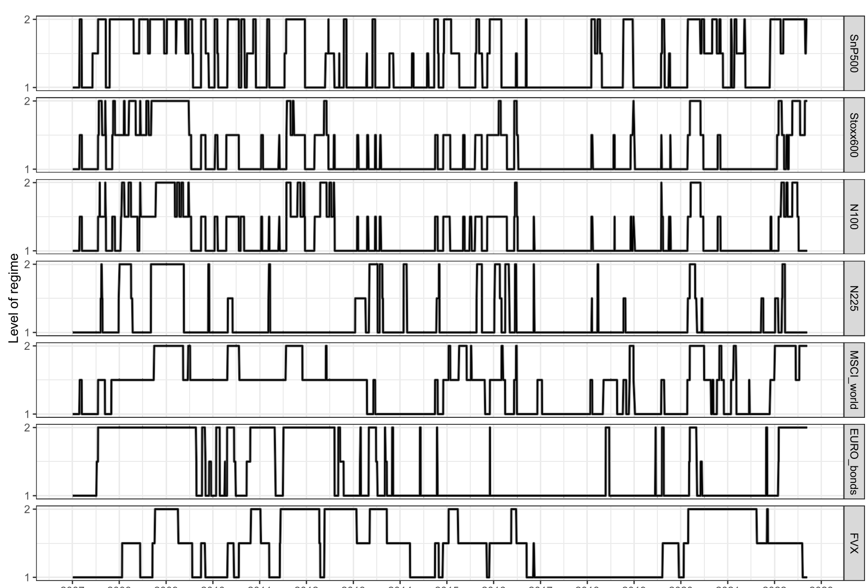

Figure 3 Identified levels of regimes (intermediate results) in each financial market using combination of states detected in Fig. 2

levels are provided that are used in the final aggregation step. If the level is above or equal to the threshold (for stocks it is 1.3 and for bonds, it is 1.5), then it is assumed that there is a shock in a particular type of financial market; otherwise, it is assumed that there is no shock. Once it is clear whether there is shock or not, final aggregation can be performed.

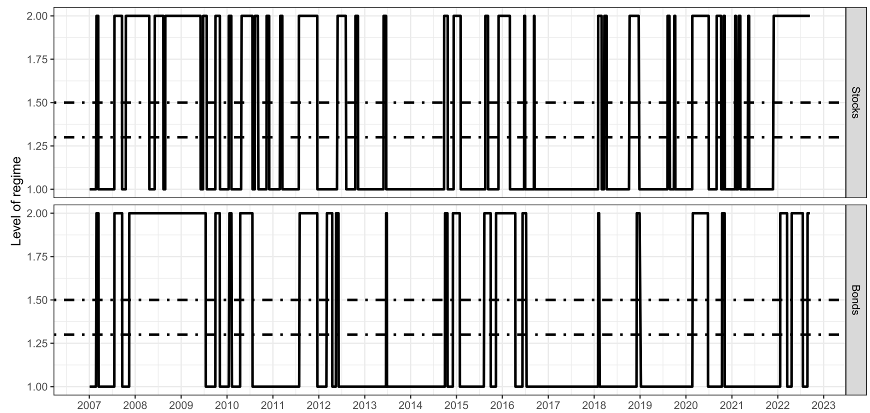

Figure 4 Identified regimes in stocks and bonds market separately (aggregation of regimes form Fig. 3). The dot-dashed lines show the threshold level (for stocks it is 1.3 and for bonds, it is 1.5)

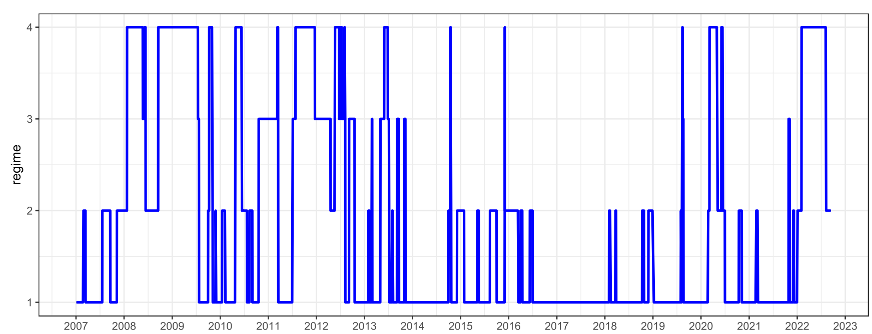

Figure 5 Final regime detected in external financial markets

Figure 5 is provided with the result of the final aggregation of the stock and bond regimes. If no shock is detected in any market, then it is assumed that on a particular day, there is Regime 1. If a shock is detected in the stock market but not in the bond, then Regime 2 is assumed. If a shock is detected on the bond market but not on stock, then Regime 3 is assumed. Finally, Regime 4 is identified in the case if a shock is detected in both types of financial markets.

For better compliance with pension fund data, this time series is truncated to the period January 2019 to September 2022 (see Fig. 6).

From Fig. 6 it is clear that Regime 1 is the most frequently observed regime during the period analysed, while Regimes 2 and 3 are the least common. It is interesting to note that Regime 4 is always led by Regime 2 (in the period 2007–2022 there are some exceptions when it is led by Regime 3). This means that large global financial crises are first reflected in stock markets and then they spill into bond markets. Moreover, Regime 4 is quite clearly seen in two cases: March through June 2020 represents the COVID-19 crisis and February through August 2022 represents the crisis caused by the Russian-Ukrainian war.

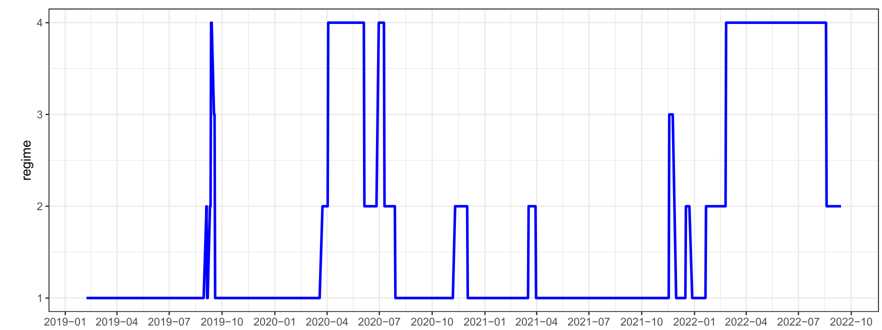

Figure 6 Regimes used in pension funds analytics (Jan 2019 – Sep 2022)

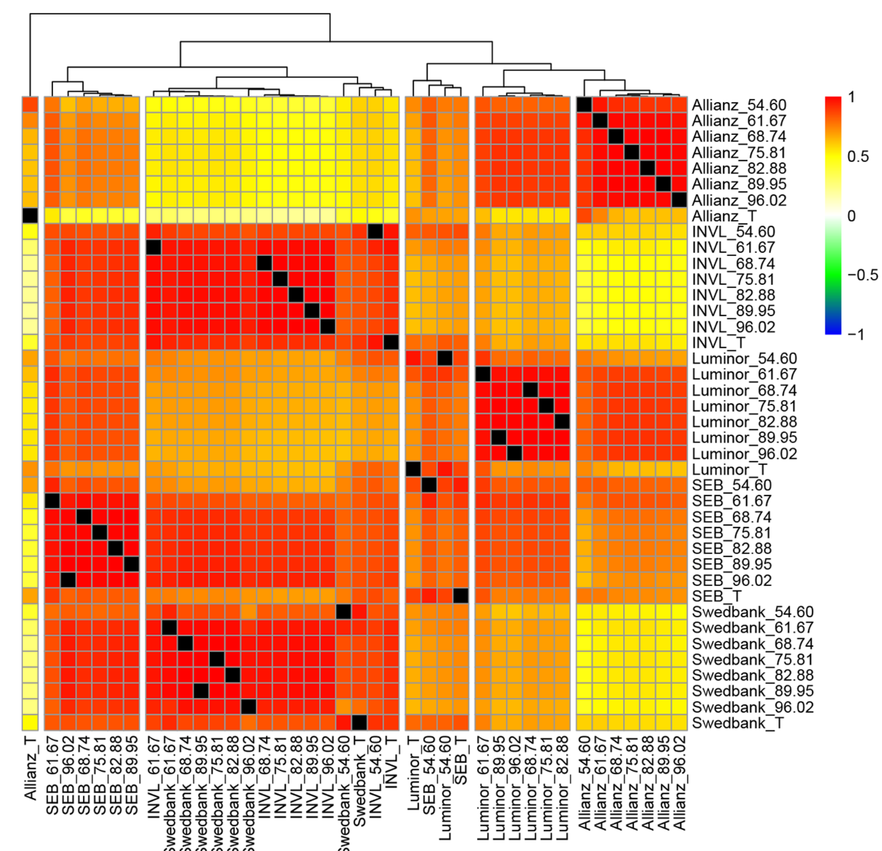

Figure 7 Clustered correlations between returns of pension funds in the entire period

4.1 Correlations and systemic risk

Next, systemic risk in the Lithuanian IInd pillar pension funds market is investigated. First, we shall take a closer look at the Pearson correlations (see Fig. 7) between the returns of pension funds in the entire period analysed.

In general, correlations are quite high and mainly exceed 1/2. The only exception is the Allianz T fund, which exhibits correlation above average only with other Allianz funds or other conservative funds (1954–1960 and T). The strongest correlations are observed

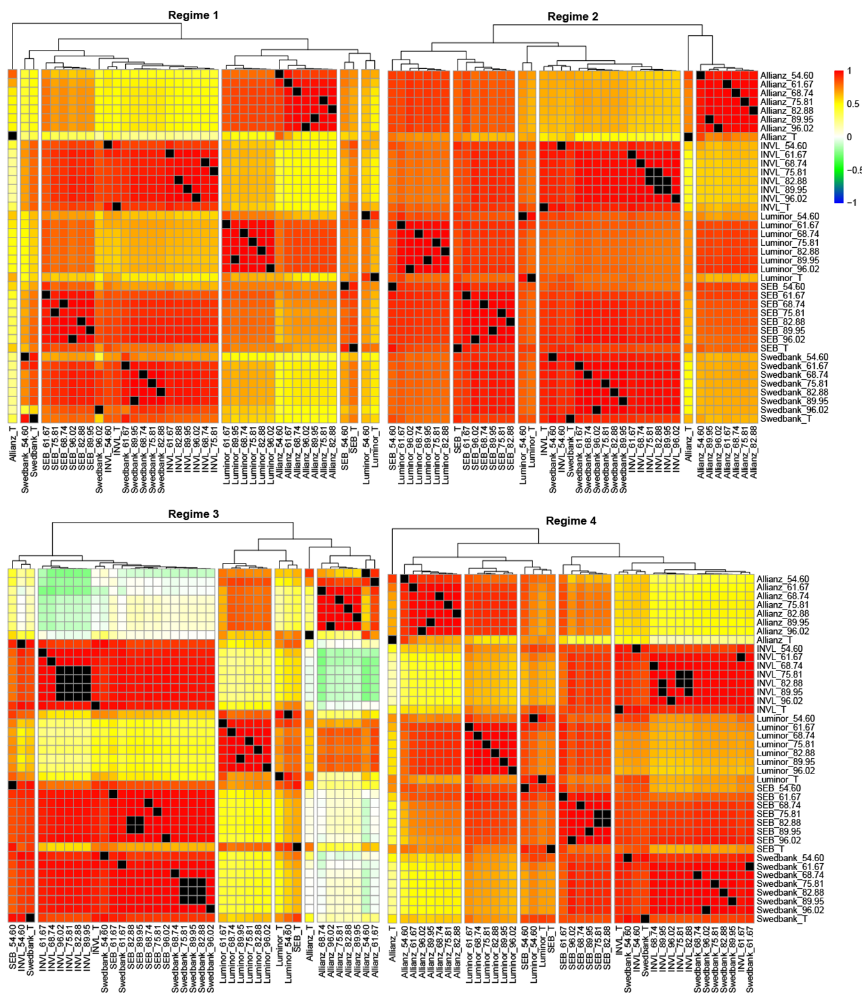

Figure 8 Correlations in Regimes 1, 2, 3 and 4

between funds of the same manager. It turns out that the correlations are linear as the [67] method provides the same results as for the Pearson correlation.

The static correlations between pension funds and financial market indices can be found in Fig. 16. From this figure, we can see that financial market indices correlate with the returns of pension funds quite differently and are mostly separated into special clusters.

Now, let us check how the correlations differ depending on the regime (see Fig. 8).

It is interesting that Allianz funds during a period of turmoil in bond markets negatively correlate with most of the other funds (the exception is with Luminor and some preservation funds). Furthermore, in this period the non-linear correlation (of Allianz) is much stronger than the Pearson correlation. However, this period is very short and results should be treated with caution. The non-linear correlation between other funds is non-significantly different from the Pearson correlation and therefore it is not necessary to use it.

From previous figures, we have observed that funds of the same manager tend to be grouped into similar clusters mainly independently of the regime. Sometimes, funds from the same age group are also assigned to similar clusters. Now let us check the group or

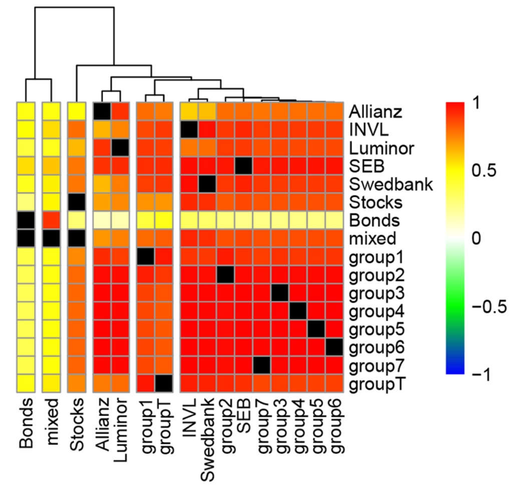

Figure 9 Multivariate correlations in the entire period

multivariate or interclass correlations [16] between these larger groups, including groups of external market indices. In Fig. 9 multivariate correlations are provided between the following groups: Allianz, INVL, Luminor, SEB, Swedbank, stocks, bonds, mixed (joint group of stocks and bonds), (oldest age) group1, (age) group2, (age) group3, (age) group4, (age) group5, (age) group6, (youngest age) group7 and (preservation) groupT.

The results of multivariate correlations reconfirm previous insights. Stock and bond indices (also mixed) correlate very differently compared to pension funds. The pension funds of Allianz and Luminor are more distant from the funds of other managers, compared to the group of the most conservative pension funds (groups 1 and T). The INVL and Swedbank funds are quite similar to SEB, which behaves more like a group of funds in the medium to young age group. Group correlations in different regimes may be found in Fig. 17 and Table 9. It turns out that interclass correlations are quite similar independently on the regime.

4.2 Causality

The correlation analysis allows us to understand how funds and market indices are related and describe systemic risk; however, it does not imply causality and dynamics. Therefore, the Granger causality (up to lag 10) is used to explain if knowing the returns of market indices may help to forecast returns of pension funds and which funds are useful in forecasting other pension fund returns. In Table 3 significant and non-significant Granger causalities between returns of financial market indices and Lithuanian pension funds are provided.

It turns out that the most important indices are SnP500, EURO bond, and FVX, which exhibit significant causality for all pension funds. A little less important are MSCI world and Stoxx600 indices, as they are non-significant for Swedbank 54–60 and T funds. The least important is N225 as it is significant only in the forecast of Allianz funds ($p > 0.05$).

Let us check which pension funds are useful in forecasting the returns of other pension funds. Table 4 shows how the columns' funds are significant in the forecasting of row funds.

Table 3 Significance of causality in forecasting rows using columns in the entire period

Fund/index	SnP500	Stoxx600	N100	N225	MSCI world	EURO bonds	FVX
Allianz_54.60	*	*	*	***	*	*	**
Allianz_61.67	*	*	*	***	*	*	*
Allianz_68.74	*	*	*	***	*	*	*
Allianz_75.81	*	*	*	***	*	*	*
Allianz_82.88	*	*	*	***	*	*	*
Allianz_89.95	*	*	*	***	*	*	*
Allianz_96.02	*	*	*	**	*	*	*
Allianz_T	*	*	*	**	*	*	**
INVL_54.60	*	*	*	***	*	*	*
INVL_61.67	*	*	**	0	*	*	*
INVL_68.74	*	*	0	0	*	**	*
INVL_75.81	*	*	***	0	*	**	*
INVL_82.88	*	*	**	0	*	*	*
INVL_89.95	*	*	**	0	*	*	*
INVL_96.02	*	*	**	0	*	*	*
INVL_T	*	**	***	0	*	*	*
Luminor_54.60	*	**	0	0	*	**	*
Luminor_61.67	*	*	*	0	*	*	*
Luminor_68.74	*	*	*	0	*	*	*
Luminor_75.81	*	*	*	0	*	*	*
Luminor_82.88	*	*	*	0	*	*	*
Luminor_89.95	*	*	*	0	*	*	*
Luminor_96.02	*	*	*	0	*	*	*
Luminor_T	*	**	***	0	*	**	*
SEB_54.60	*	*	*	0	*	*	*
SEB_61.67	*	*	*	0	*	*	*
SEB_68.74	*	*	*	0	*	*	*
SEB_75.81	*	*	*	0	*	*	*
SEB_82.88	*	*	*	0	*	*	*
SEB_89.95	*	*	*	0	*	*	*
SEB_96.02	*	*	*	0	*	*	*
SEB_T	*	**	**	0	*	*	*
Swedbank_54.60	***	0	0	0	0	*	*
Swedbank_61.67	*	**	0	0	*	*	*
Swedbank_68.74	*	*	**	0	*	*	*
Swedbank_75.81	*	*	**	0	*	*	*
Swedbank_82.88	*	*	**	0	*	*	*
Swedbank_89.95	*	*	**	0	*	*	*
Swedbank_96.02	*	*	**	0	*	*	*
Swedbank_T	***	*	**	0	0	*	*
SnP500	*	*	*	*	*	*	*
Stoxx600	*	*	0	0	*	*	*
N100	*	0	*	0	*	**	*
N225	*	*	*	*	*	*	*
MSCI world	*	*	*	0	*	*	*
EURO bonds	*	***	***	0	*	*	**
FVX	*	*	*	*	*	0	*

Note. * - significant with $p < 0.01$, ** - significant with $p < 0.05$, *** - significant with $p < 0.10$, 0 - non-significant with $p > 0.10$.

It is not surprising that preservation (T) funds and funds from the oldest age group (54–60) are least important in forecasting the returns of other funds; moreover, their returns are least impacted by other funds. The rare exceptions are Luminor funds (T and 54–60) which are significantly important in forecasting returns. Interestingly, the returns of the Allianz T fund can be forecasted using the returns of all other funds. Another interesting thing is that it is less important to use the returns of the same manager than to use the returns of funds of other managers. This is very expressed for Swedbank funds, but

Table 4 Significance of Granger causality between Lithuanian pension funds in entire period

	Allianz_54.60	Allianz_61.67	Allianz_68.74	Allianz_75.81	Allianz_82.88	Allianz_89.95	Allianz_96.02	Allianz_T	INVL_54.60	INVL_61.67	INVL_68.74	INVL_75.81	INVL_82.88	INVL_89.95	INVL_96.02	INVL_T	Luminor_54.60	Luminor_61.67	Luminor_68.74	Luminor_75.81	Luminor_82.88	Luminor_89.95	Luminor_96.02	Luminor_T	SEB_54.60	SEB_61.67	SEB_68.74	SEB_75.81	SEB_82.88	SEB_89.95	SEB_96.02	SEB_T	Swedbank_54.60	Swedbank_61.67	Swedbank_68.74	Swedbank_75.81	Swedbank_82.88	Swedbank_89.95	Swedbank_96.02	Swedbank_T
Allianz_54.60	*	0	0	0	0	0	0	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Allianz_61.67	0	*	**	**	***	**	0	***	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Allianz_68.74	***	**	*	0	0	0	**	***	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Allianz_75.81	**	**	**	*	*	*	*	**	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Allianz_82.88	***	***	0	*	*	0	*	***	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Allianz_89.95	0	***	0	*	0	*	**	***	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Allianz_96.02	***	0	0	0	0	0	*	**	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Allianz_T	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
INVL_54.60	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	**	*	*	*	*	*	*	0	*	*	*	*	*	*	**	*
INVL_61.67	*	*	*	*	*	*	*	*	*	*	0	0	***	***	***	***	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	***	0	*	*	*	*	*	0	**
INVL_68.74	*	*	*	*	*	*	*	*	**	0	*	0	0	0	0	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	**	0	0	***	**	**	**	***	0
INVL_75.81	*	*	*	*	*	*	*	*	***	0	0	*	0	0	0	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	**	0	0	0	**	**	**	***	0
INVL_82.88	*	*	*	*	*	*	*	*	**	***	0	0	*	**	**	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	**	0	0	**	*	*	*	***	0
INVL_89.95	*	*	*	*	*	*	*	*	**	***	0	0	**	*	***	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	**	0	0	**	*	*	*	***	0
INVL_96.02	*	*	*	*	*	*	*	*	**	***	0	0	***	***	*	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	**	0	0	**	*	*	*	***	0
INVL_T	*	*	*	*	*	*	*	*	0	**	**	**	**	**	**	*	*	*	*	**	**	**	*	*	**	*	**	***	**	**	**	0	0	***	**	***	***	**	0	0
Luminor_54.60	*	*	*	*	*	*	*	**	0	0	**	*	*	*	*	0	*	*	*	*	*	*	*	*	0	*	*	*	*	*	*	0	0	*	*	*	*	*	**	0
Luminor_61.67	*	*	*	*	*	*	*	***	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	0	**	*	*	*	*	*	0	*	*	*	*	*	*	*	*
Luminor_68.74	**	*	*	*	*	*	*	***	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	***	*	*	*	*	*	*	***1	*	*	*	*	*	*	*	*
Luminor_75.81	**	*	*	*	*	*	*	***	*	*	*	*	*	*	*	*	*	*	*	*	*	**	***	*	**	*	*	*	*	*	*	***	*	*	*	*	*	*	*	*
Luminor_82.88	**	*	*	*	*	*	*	***	*	*	*	*	*	*	*	*	*	*	*	*	*	*	***	*	**	*	*	*	*	*	*	**	*	*	*	*	*	*	*	*
Luminor_89.95	**	*	*	*	*	*	*	***	*	*	*	*	*	*	*	*	*	*	*	*	**	***	*	*	**	*	*	*	*	*	*	**	*	*	*	*	*	*	*	*
Luminor_96.02	**	*	*	*	*	*	*	***	*	*	*	*	*	*	*	*	*	*	*	*	*	*	***	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Luminor_T	*	*	*	*	*	*	*	*	0	***	*	*	*	*	*	0	*	*	*	*	*	*	*	*	***	*	*	*	*	*	*	**	0	*	*	*	*	*	**	0

Table 4 (*Continued*)

	Allianz_54.60	Allianz_61.67	Allianz_68.74	Allianz_75.81	Allianz_82.88	Allianz_89.95	Allianz_96.02	Allianz_T	INVL_54.60	INVL_61.67	INVL_68.74	INVL_75.81	INVL_82.88	INVL_89.95	INVL_96.02	INVL_T	Luminor_54.60	Luminor_61.67	Luminor_68.74	Luminor_75.81	Luminor_82.88	Luminor_89.95	Luminor_96.02	Luminor_T	SEB_54.60	SEB_61.67	SEB_68.74	SEB_75.81	SEB_82.88	SEB_89.95	SEB_96.02	SEB_T	Swedbank_54.60	Swedbank_61.67	Swedbank_68.74	Swedbank_75.81	Swedbank_82.88	Swedbank_89.95	Swedbank_96.02	Swedbank_T
SEB_54.60	*	*	*	*	*	*	*	0	**	***	**	**	**	**	**	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	0	0	*	*	*	*	*	**	**
SEB_61.67	**	*	*	*	*	*	*	***	**	*	*	*	*	*	*	***	*	*	*	*	*	*	*	*	0	*	*	*	*	*	*	0	0	*	*	*	*	*	*	***
SEB_68.74	*	*	*	*	*	*	*	**	*	*	*	*	*	*	*	**	*	*	*	*	*	*	*	*	***	*	*	0	0	0	**	0	0	*	*	*	*	*	**	***
SEB_75.81	*	*	*	*	*	*	*	**	**	*	*	*	*	*	*	**	*	*	*	*	*	*	*	*	0	*	0	*	0	***	*	0	0	*	*	*	*	*	**	0
SEB_82.88	*	*	*	*	*	*	*	**	**	*	*	*	*	*	*	**	*	*	*	*	*	*	*	*	***	*	0	0	*	0	*	0	0	*	*	*	*	*	**	0
SEB_89.95	*	*	*	*	*	*	*	**	**	*	*	*	*	*	*	**	*	*	*	*	*	*	*	*	0	*	0	0	0	*	*	0	0	*	*	*	*	*	**	0
SEB_96.02	*	*	*	*	*	*	*	*	**	*	*	*	*	*	*	**	*	*	*	*	*	*	*	*	***	*	**	0	*	*	*	0	0	**	*	*	*	*	***	0
SEB_T	*	*	*	*	*	*	*	*	**	0	0	0	0	0	0	***	*	*	*	*	*	*	*	*	*	*	*	**	**	**	**	*	0	**	***	0	0	***	0	**
Swedbank_54.60	**	***	***	***	***	***	**	**	0	0	0	0	0	0	0	0	*	***	0	0	0	0	***	*	***	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0
Swedbank_61.67	*	*	*	*	*	*	*	*	**	*	0	0	0	0	0	0	*	*	*	*	*	*	*	*	*	*	*	**	*	*	**	**	0	*	0	0	0	0	0	0
Swedbank_68.74	*	*	*	*	*	*	*	*	*	*	**	***	**	**	**	***	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	0	0	*	0.	0	0	0	0
Swedbank_75.81	*	*	*	*	*	*	*	*	**	*	**	**	*	*	*	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	**	0	0	0	*	0	0	0	0
Swedbank_82.88	*	*	*	*	*	*	*	*	**	*	**	**	*	*	*	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	**	0	0	0	0	*	0	0	0
Swedbank_89.95	*	*	*	*	*	*	*	*	**	*	**	*	*	*	*	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	**	0	0	0	0	0	*	0	0
Swedbank_96.02	*	*	*	*	*	*	*	*	***	**	0	0	0	0	0	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	**	**	0	0	0	0	0	0	*	0
Swedbank_T	*	**	**	***	**	**	*	*	***	*	*	*	*	*	*	0	*	0	0	0	0	0	0	*	0	0	0	0	***	***	***	0	0	*	**	*	*	*	0	*

Note. * - significant with $p < 0.01$, ** - significant with $p < 0.05$, *** - significant with $p < 0.10$, **0** - non-significant with $p > 0.10$.

for Luminor is the opposite situation. Therefore, Luminor funds are useful in forecasting the returns of all funds and are influenced by all. It turns out that forecasting of returns of Swedbank funds is weakly impacted by returns of INVL and vice versa, which is a surprise because they exhibit very strong correlations and typically are clustered into similar groups (see results on correlation).

Generally speaking, knowing the historical returns of the pension fund and the historical returns of funds from other managers is useful in measuring systemic risk.

However, these assumptions may not be true under stressed market regimes. Let us take a look at Granger causality (Table 5) in Regimes 1, 2 and 4 (Regime 3 is too short for Granger analysis).

It is unexpected that N225 has no significance (with the exception of some Allianz funds in Regime 2) in forecasting other returns independently on the regime. It is a little bit surprising that the FVX and EURO bond indices are not useful for most of the funds even during the no-stress regime (significant only for some conservative funds). However, FVX becomes important in Regime 4, as it can be useful for forecasting the returns of the majority of Swedbank funds.

Special attention should be paid to Regime 2 during which only Allianz funds could be forecasted (with significance $p < 0.1$) while the other returns cannot be forecasted using market indices. N100 is also not very useful for forecasting in Regime 4.

The significance of the Granger causality between PFs in different regimes can be found in Tables 10, 11 and 12 respectively.

This suggests that information transfer from market to market is quite dependent on the period analysed, and stock indices are more useful than bond indices. This is not a surprise, because pension funds mainly invest in stocks rather than bonds.

4.3 Spillover

Finally, the returns spillover is analysed. The internal spillover between Lithuanian IInd pillar pension funds (i.e., without the influence of external indices) is first presented. Such an analysis is important for pension system participants, market supervision authorities (Bank of Lithuania) and policymakers (government and parliament). Participants (investors) are less interested in what happens outside their decision-making radar (narrow point of view). They simply expect higher returns from the pension fund in which they have invested. Return spillover generators could be their choice as these funds lead the market. However, the Bank of Lithuania and the government are more interested in the sustainability and resilience of the entire pension system. Therefore, they try to keep the market less concentrated, less connected, and more resilient to external shocks. See Sect. 4.3.1 for a broader view of spillover analysis between pension funds and external market indices.

In Fig. 10 are provided graph representations of spillover in the period Jan. 2019–Sep. 2022, using the VECM model (VAR case is provided in Fig. 18 (A)).

The arrows in this figure show the direction of spillover from one fund to another. The wider the arrow, the more spillover is transferred. The size of the nodes indicates the net spillover for a particular pension fund, while the colour shows if the fund is the generator (green) or the absorber (red) of the spillover.

In Fig. 11 are provided graph representations of spillover in different regimes, using the VECM model (VAR case is given in Fig. 18 (B), (C) and (D)).

Table 5 Significance of Granger causality in Regimes 1, 2 and 4

Fund/index	Regime 1							Regime 2							Regime 4						
	SnP500	Stoxx600	N100	N225	MSCI_world	EURO_bonds	FVX	SnP500	Stoxx600	N100	N225	MSCI_world	EURO_bonds	FVX	SnP500	Stoxx600	N100	N225	MSCI_world	EURO_bonds	FVX
Allianz_54.60	*	*	*	0	*	0	0	0	0	0	0	0	0	**	*	**	**	0	*	0	0
Allianz_61.67	*	*	*	0	*	0	0	***	0	0	**	**	0	0	*	**	***	0	*	0	0
Allianz_68.74	*	*	*	0	*	0	0	***	0	0	**	**	0	0	*	**	0	0	*	0	0
Allianz_75.81	*	*	*	0	*	0	0	***	0	0	***	**	0	0	*	**	0	0	*	0	0
Allianz_82.88	*	*	*	0	*	0	0	***	0	0	***	**	0	0	*	**	0	0	*	0	0
Allianz_89.95	*	*	*	0	*	0	0	**	0	0	***	**	0	0	*	**	0	0	*	0	0
Allianz_96.02	*	*	*	0	*	0	0	0	0	0	**	**	0	0	*	**	0	0	*	0	0
Allianz_T	*	*	**	0	*	**	***	0	0	0	0	0	0	0	**	**	**	0	***	0	0
INVL_54.60	**	**	**	0	0	***	0	0	0	0	0	0	0	0	**	0	0	0	**	0	**
INVL_61.67	**	0	0	0	***	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
INVL_68.74	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**	0	0
INVL_75.81	***	0	0	0	***	0	0	0	0	0	0	0	0	0	0	0	0	0	**	0	0
INVL_82.88	**	0	0	0	**	0	0	0	0	0	0	0	0	0	0	0	0	0	**	0	0
INVL_89.95	**	0	0	0	**	0	0	0	0	0	0	0	0	0	0	0	0	0	**	0	0
INVL_96.02	**	0	0	0	**	0	0	0	0	0	0	0	0	0	0	0	0	0	**	0	0
INVL_T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*
Luminor_54.60	**	0	0	0	**	0	0	0	***	0	0	0	0	0	***	0	0	0	***	0	***
Luminor_61.67	*	***	0	0	*	0	0	0	0	0	0	0	0	0	**	0	0	0	***	0	0
Luminor_68.74	*	**	***	0	*	0	0	0	0	0	0	0	0	0	**	0	0	0	*	0	0
Luminor_75.81	*	**	***	0	*	0	0	0	0	0	0	0	0	0	**	0	0	0	*	0	0
Luminor_82.88	*	**	**	0	*	0	0	0	0	0	0	0	0	0	*	0	0	0	*	0	0
Luminor_89.95	*	**	**	0	*	0	0	0	0	0	0	0	0	0	**	0	0	0	*	0	0
Luminor_96.02	*	**	**	0	*	0	0	0	0	0	0	0	0	0	**	0	0	0	**	0	0
Luminor_T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SEB_54.60	*	0	0	0	*	0	0	0	0	0	0	0	0	0	**	0	0	0	**	0	0
SEB_61.67	*	0	0	0	*	0	0	0	0	0	0	0	0	0	**	0	0	0	**	0	**
SEB_68.74	*	***	0	0	*	0	0	0	0	0	0	0	0	0	**	0	0	0	**	0	***
SEB_75.81	*	***	0	0	*	0	0	0	0	0	0	0	0	0	***	0	0	0	**	0	0
SEB_82.88	*	***	0	0	*	0	0	0	0	0	0	0	0	0	***	0	0	0	**	0	0
SEB_89.95	*	***	0	0	*	0	0	0	0	0	0	0	0	0	***	0	0	0	**	0	0
SEB_96.02	*	***	0	0	*	0	0	0	0	0	0	0	0	0	***	0	0	0	**	0	0
SEB_T	*	0	0	0	*	0	0	0	0	0	0	0	0	0	***	0	0	0	0	0	0
Swedbank_54.60	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**
Swedbank_61.67	***	0	0	0	***	0	0	0	0	0	0	0	0	0	0	0	0	0	***	0	**
Swedbank_68.74	**	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	**	0	***
Swedbank_75.81	**	0	0	0	*	0	0	0	0	0	0	0	0	0	0	**	0	0	**	0	***
Swedbank_82.88	**	0	0	0	*	0	0	0	0	0	0	0	0	0	0	**	0	0	**	0	***
Swedbank_89.95	**	0	0	0	*	0	0	0	0	0	0	0	0	0	0	**	0	0	**	0	***
Swedbank_96.02	*	**	0	0	*	0	0	0	0	0	0	0	0	0	0	**	0	0	**	0	0
Swedbank_T	0	0	0	0	0	**	0	0	0	0	0	0	0	0	0	**	0	0	0	0	***
SnP500	*	0	0	0	***	0	0	*	0	0	0	0	0	0	*	0	0	0	0	0	0
Stoxx600	0	*	0	0	0	0	0	0	*	0	0	0	0	0	***	*	0	0	**	0	0
N100	0	0	*	0	0	0	0	0	0	*	0	0	0	0	0	0	**	0	0	0	0
N225	*	*	*	*	*	0	***	0	0	0	*	0	0	0	*	*	**	*	*	0	0
MSCI_world	0	0	0	0	*	0	0	0	0	0	0	*	0	0	0	0	0	0	*	0	0
EURO_bonds	0	**	**	0	0	*	0	0	0	0	0	0	*	0	0	0	0	0	0	*	0
FVX	0	0	0	0	0	0	*	0	***	***	0	0	0	*	***	0	0	**	0	0	*

Note. * - significant with $p < 0.01$, ** - significant with $p < 0.05$, *** - significant with $p < 0.10$, 0 - non-significant with $p > 0.10$.

From these figures, we can see that transfer of spillover heavily depends on the period and regime analysed. Now, let us check which funds are spillover generators and which are absorbers in Lithuania. In Table 6 are provided "net", "from" and "to" spillover estimates in different periods (entire period and Regimes 1, 2 and 4) using VECM models (up to lag 2).

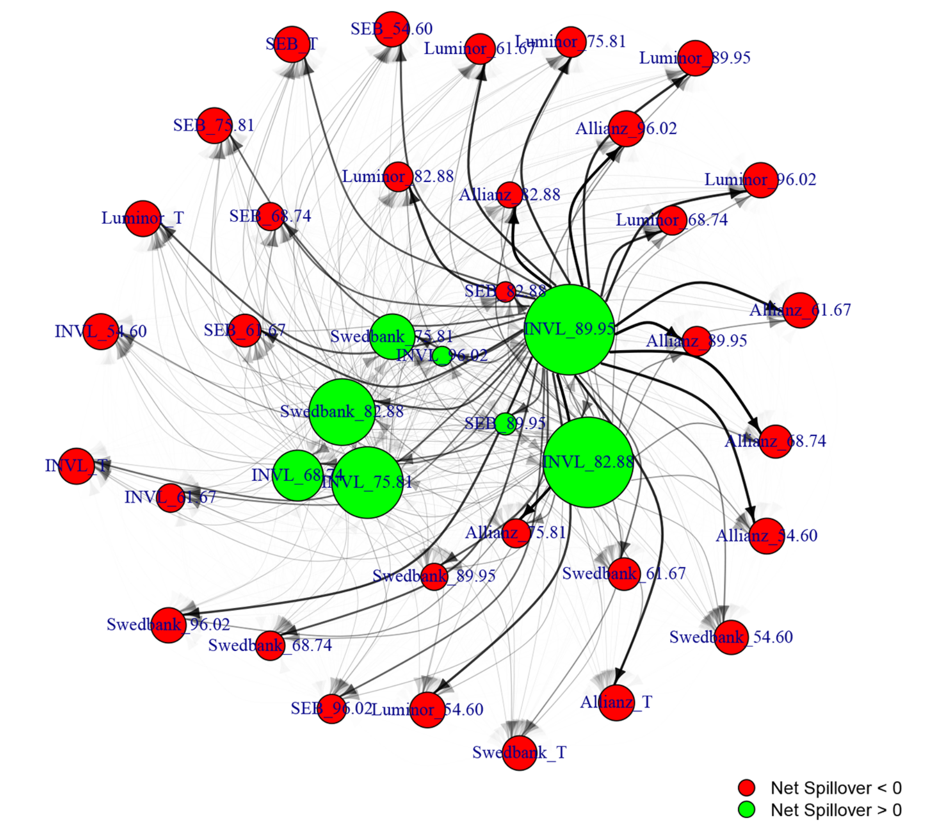

Figure 10 Spillover network in the entire period Jan. 2019–Sep. 2022, using VECM

From this table, we can see that net spillover is negative for all Allianz and Luminor funds independently of the regime. It is even negative for some more conservative and most stock funds of INVL, SEB and Swedbank. Although it is only positive for INVL, SEB and Swedbank funds in the age group of participants that are born in 1975–1995 (with some exceptions). Throughout the period, the VECM spillover leader is INVL 89–95. However, there are some differences during market Regimes 1, 2 and 4. In Regime 1, the largest spillover is observed for Swedbank 82–88, when it slightly exceeds INVL 75–81. Furthermore, Swedbank 89–95 becomes a significant leader in Regime 2 (more than 6 times greater spillover than in the second position). It is interesting that in Regime 4 Swedbank 82–88 becomes the largest spillover generator, leaving SEB 89–95 in the second position. In general, according to the VECM model, Swedbank is the largest spillover generator, leaving the INVL in the second position.

Similar behaviour can be observed in the case of the VAR method (see Table 13). The greatest spillover (the entire period) is observed for INVL 89–95, and the same situation remains in Regime 1. During Regime, 2 spillover leader becomes INVL 75–81 and during Regime 4 it switches to INVL 82–88. In general, INVL stock funds are the largest spillover generators (Swedbank is in the second position) according to the VAR method.

Regardless of the method used, Allinaz and Lunminor funds are spillover absorbers, and Swedbank and INVL are spillover generators. According to Table 1, Swedbank and INVL manage above 50% of all assets. This indicates two things: first, the pension funds market is not concentrated, but second, the market is exposed to the spillover generated by

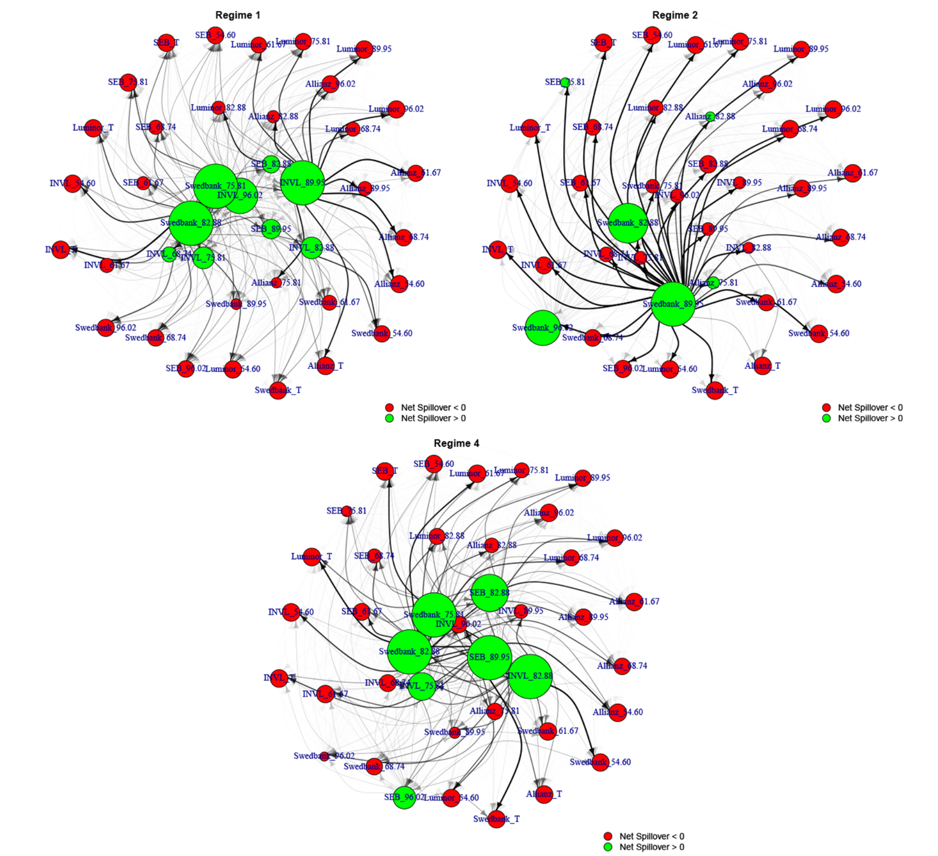

Figure 11 Spillover networks in different Regimes (no crisis, stock crisis, global financial crisis) using VECM models

two fund managers. In normal periods (Regime 1) this is not a problem; however, during shock periods the entire market can be dragged down. Therefore, policy makers should pay attention to the connectedness between funds.

In Fig. 12 dynamics of overall spillover (VECM) between pension funds are provided using rolling time windows (120 days).

According to this figure, there is no clear relation between the levels of overall spillover and the regime. However, lower levels are typically observed during Regime 1, while rapid changes are more observed during regimes with shocks. This is not surprising because regimes are identified using external data not directly related to the returns of Lithuanian pension funds. A similar result is obtained using the VAR technique (see Fig. 20).

In the next subsection, a spillover effect is explored when not only information from the Lithuanian pension fund market is included, but information from the global financial market is also used.

4.3.1 Spillover in the PF market when external market indices included

Now, let us check how the spillover changes if external market indices are included. In Fig. 13 graph representations of spillover in the period Jan. 2019–Sep. 2022 are provided, using VECM models for the full data set (VAR models are not discussed).

From this figure, we can see that INVL funds 82–88 and 89–95 remain the largest spillover generators (compared to Fig. 10). They are followed by Swedbank 82–88 and

Table 6 Spillover (net, from and to) between pension funds using VECM model with full cointegration

Fund	Entire period			Regime 1			Regime 2			Regime 4		
	Net	From	To	Net	From	To	Net	From	To	Net	From	To
Allianz_54.60	−2.44	0.06	2.50	−2.37	0.09	2.47	−2.49	0.01	2.50	−2.49	0.005	2.50
Allianz_61.67	−2.36	0.13	2.50	−2.08	0.41	2.50	−2.48	0.01	2.49	−2.46	0.04	2.50
Allianz_68.74	−2.06	0.42	2.48	−2.17	0.33	2.50	−2.34	0.16	2.50	−2.16	0.31	2.47
Allianz_75.81	−1.51	0.98	2.49	−0.45	1.95	2.40	0.90	3.34	2.44	−2.12	0.38	2.50
Allianz_82.88	−1.09	1.38	2.48	−0.98	1.52	2.50	0.24	2.69	2.45	−1.64	0.83	2.47
Allianz_89.95	−1.60	0.89	2.48	−1.44	0.96	2.40	−2.28	0.18	2.47	−2.16	0.32	2.48
Allianz_96.02	−2.45	0.05	2.50	−2.36	0.13	2.49	−2.42	0.07	2.50	−2.44	0.05	2.49
Allianz_T	−2.47	0.03	2.50	−2.48	0.01	2.49	−2.49	0.003	2.50	−2.50	0.001	2.50
INVL_54.60	−2.46	0.04	2.50	−2.45	0.04	2.49	−2.49	0.01	2.50	−2.50	0.001	2.50
INVL_61.67	−1.44	1.03	2.47	−1.53	0.82	2.35	−2.31	0.18	2.50	−2.44	0.06	2.50
INVL_68.74	4.53	6.87	2.34	1.75	4.14	2.39	−1.64	0.86	2.50	−2.28	0.21	2.49
INVL_75.81	7.38	9.69	2.31	3.66	5.71	2.04	−1.17	1.30	2.47	5.31	7.32	2.01
INVL_82.88	11.66	13.84	2.19	3.65	5.91	2.26	−0.65	1.85	2.49	10.50	12.22	1.71
INVL_89.95	27.94	29.86	1.92	13.47	15.92	2.45	−0.95	1.49	2.44	−1.47	0.98	2.45
INVL_96.02	0.23	2.62	2.38	7.53	9.81	2.29	−1.37	1.13	2.50	−2.25	0.24	2.49
INVL_T	−2.47	0.03	2.50	−2.47	0.02	2.49	−2.50	0.004	2.50	−2.49	0.01	2.50
Luminor_54.60	−2.42	0.08	2.50	−2.39	0.07	2.46	−2.49	0.01	2.50	−2.48	0.02	2.50
Luminor_61.67	−1.74	0.75	2.49	−1.97	0.44	2.42	−2.32	0.18	2.50	−2.45	0.04	2.49
Luminor_68.74	−1.56	0.92	2.48	−1.48	0.92	2.40	−2.48	0.02	2.50	−2.04	0.44	2.48
Luminor_75.81	−1.73	0.75	2.49	−2.16	0.32	2.48	−2.37	0.13	2.50	−1.71	0.77	2.48
Luminor_82.88	−1.60	0.88	2.48	−1.24	1.26	2.50	−1.82	0.66	2.48	−2.02	0.47	2.49
Luminor_89.95	−2.39	0.11	2.50	−2.45	0.02	2.48	−2.20	0.30	2.50	−2.14	0.36	2.49
Luminor_96.02	−2.36	0.14	2.50	−2.37	0.11	2.49	−2.41	0.09	2.49	−2.19	0.30	2.49
Luminor_T	−2.45	0.05	2.50	−2.42	0.02	2.44	−2.50	0.002	2.50	−2.49	0.01	2.50
SEB_54.60	−2.36	0.13	2.50	−2.27	0.22	2.50	−2.41	0.09	2.50	−2.48	0.02	2.50
SEB_61.67	−2.02	0.47	2.49	−1.24	1.16	2.40	−2.00	0.48	2.48	−2.27	0.23	2.50
SEB_68.74	−1.37	1.10	2.48	−1.49	1.01	2.50	−1.95	0.54	2.49	−1.47	0.97	2.44
SEB_75.81	−2.44	0.06	2.50	−2.36	0.14	2.50	0.24	2.68	2.44	−0.51	1.92	2.43
SEB_82.88	−0.32	2.12	2.44	2.41	4.71	2.29	−2.44	0.06	2.50	8.00	10.36	2.36
SEB_89.95	0.55	2.96	2.41	2.98	5.40	2.42	−1.10	1.36	2.45	14.52	16.91	2.39
SEB_96.02	−1.52	0.95	2.47	−2.20	0.26	2.46	−2.39	0.11	2.50	3.87	6.17	2.29
SEB_T	−2.48	0.02	2.50	−2.37	0.08	2.46	−2.47	0.02	2.50	−2.50	0.001	2.50
Swedbank_54.60	−2.23	0.27	2.50	−2.13	0.34	2.48	−2.47	0.03	2.50	−2.41	0.09	2.50
Swedbank_61.67	−1.99	0.49	2.48	−1.70	0.74	2.44	−2.07	0.42	2.49	−2.44	0.06	2.50
Swedbank_68.74	−1.56	0.92	2.47	−2.15	0.33	2.47	−2.22	0.26	2.49	−2.19	0.31	2.50
Swedbank_75.81	3.78	6.14	2.36	10.50	12.48	1.97	−1.37	1.09	2.46	10.06	12.33	2.26
Swedbank_82.88	6.70	8.95	2.25	14.55	16.61	2.05	8.69	10.87	2.18	16.07	18.41	2.34
Swedbank_89.95	−1.23	1.23	2.46	−0.55	1.79	2.34	54.04	55.05	1.01	−0.66	1.79	2.46
Swedbank_96.02	−2.37	0.13	2.50	−2.35	0.13	2.48	7.45	9.67	2.22	−0.08	2.37	2.45
Swedbank_T	−2.28	0.21	2.49	−2.40	0.05	2.45	−2.50	0.003	2.50	−2.42	0.07	2.49

SEB 89–95. However, INVL 65–74 and 75–84 lost their importance. The really interesting observation is that all financial market indices are spillover absorbers. In general, the inclusion of these indices did not change the structure of the spillover network in the entire period. In Table 7 are provided net, from and to spillovers in different regimes.

Results from this table reconfirm assumptions from Fig. 10 and Table 6: INVL and Swedbank funds are the largest spillover generators, while Allianz and Luminor are absorbers. What is really surprising is that indices of financial markets are spillover absorbers independent of the regime. The graphic interpretation of the spillover network in different regimes is provided in Fig. 19.

Figure 14 provides the dynamics of the overall spillover (VECM) between all data sets using rolling time windows (120 days).

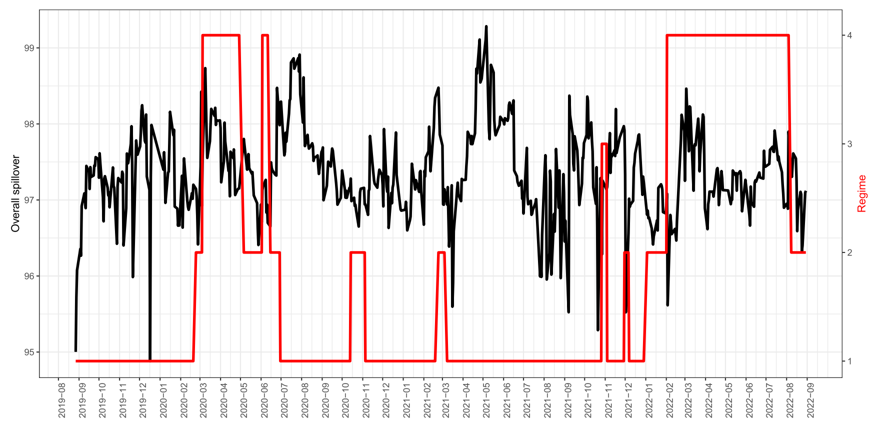

Figure 12 Overall VECM spillover between pension funds using a rolling window of 120 days

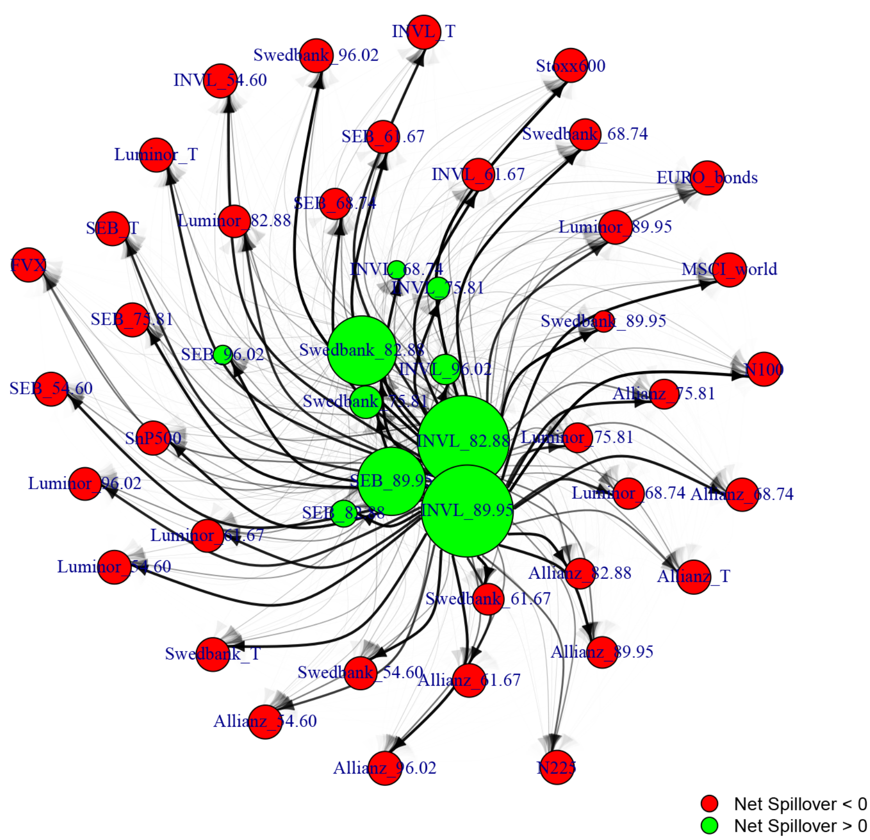

Figure 13 Spillover network in the entire period Jan. 2019–Sep. 2022, using VECM models (including market indices)

Once again, from this figure, there is no clear dependence between the overall spillover and the regime. Moreover, higher levels of spillover are not observed during stress periods. Furthermore, a separate analysis of the overall spillover between the financial market indices (see Fig. 15) shows that higher levels of spillover are observed during global financial crises, while lower levels indicate a normal market regime.

Table 7 Spillover (net, from and to) between pension funds and market indices using VECM model with full cointegration

Fund	Entire period			Regime 1			Regime 2			Regime 4		
	Net	From	To	Net	From	To	Net	From	To	Net	From	To
Allianz_54.60	−2.10	0.03	2.13	−2.01	0.07	2.08	−2.10	0.02	2.13	−2.12	0.002	2.12
Allianz_61.67	−2.06	0.07	2.13	−1.60	0.52	2.12	−2.09	0.04	2.13	−2.11	0.01	2.12
Allianz_68.74	−2.01	0.12	2.12	−1.93	0.16	2.10	−2.09	0.03	2.12	−2.12	0.01	2.12
Allianz_75.81	−1.54	0.58	2.12	−1.49	0.60	2.09	−1.11	1.01	2.12	−1.43	0.69	2.12
Allianz_82.88	−1.65	0.46	2.12	−1.57	0.56	2.13	−0.42	1.66	2.12	−1.60	0.53	2.12
Allianz_89.95	−1.78	0.34	2.12	−1.49	0.55	2.04	−2.04	0.09	2.12	−2.10	0.01	2.12
Allianz_96.02	−2.09	0.04	2.13	−2.09	0.02	2.12	−2.11	0.01	2.13	−2.07	0.001	2.07
Allianz_T	−2.12	0.01	2.13	−2.09	0.005	2.09	−2.12	0.01	2.13	−2.12	0.001	2.13
INVL_54.60	−2.11	0.02	2.13	−2.08	0.03	2.12	−2.11	0.02	2.13	−2.12	0.004	2.12
INVL_61.67	−1.93	0.19	2.12	−0.65	1.34	1.99	−1.74	0.39	2.12	−1.16	0.95	2.11
INVL_68.74	0.01	2.09	2.09	4.82	6.79	1.97	1.04	3.09	2.09	2.68	4.61	1.92
INVL_75.81	0.60	2.68	2.07	7.46	9.13	1.67	5.89	7.90	2.07	0.57	2.70	2.12
INVL_82.88	15.97	17.74	1.77	3.91	5.77	1.87	11.49	13.42	1.77	9.94	11.77	1.84
INVL_89.95	36.66	37.92	1.26	3.11	5.23	2.13	11.27	13.13	1.26	17.55	19.00	1.45
INVL_96.02	1.62	3.65	2.03	5.16	7.15	1.98	−1.77	0.35	2.03	2.59	4.60	2.00
INVL_T	−2.12	0.01	2.13	−2.09	0.03	2.12	−2.09	0.04	2.13	−2.11	0.01	2.12
Luminor_54.60	−2.08	0.05	2.13	−2.03	0.07	2.10	−2.12	0.004	2.13	−2.10	0.02	2.12
Luminor_61.67	−1.96	0.16	2.12	−1.64	0.42	2.06	−2.05	0.07	2.12	−1.84	0.29	2.13
Luminor_68.74	−1.74	0.38	2.12	−1.40	0.70	2.10	−1.77	0.35	2.12	−1.80	0.32	2.12
Luminor_75.81	−1.54	0.58	2.12	−1.16	0.96	2.12	−1.84	0.28	2.12	−0.46	1.61	2.08
Luminor_82.88	−1.90	0.22	2.12	−1.48	0.65	2.13	−1.85	0.27	2.12	2.16	4.27	2.11
Luminor_89.95	−2.08	0.04	2.13	−2.09	0.02	2.11	2.50	4.50	2.13	−1.10	1.02	2.12
Luminor_96.02	−1.94	0.18	2.12	−2.00	0.11	2.12	0.81	2.85	2.12	−1.95	0.17	2.12
Luminor_T	−2.11	0.02	2.13	−2.07	0.01	2.08	−2.11	0.02	2.13	−2.12	0.002	2.12
SEB_54.60	−2.10	0.03	2.13	−1.96	0.16	2.13	−2.04	0.08	2.13	−2.09	0.03	2.12
SEB_61.67	−1.96	0.17	2.12	−1.42	0.68	2.10	−1.58	0.54	2.12	−1.93	0.19	2.13
SEB_68.74	−1.72	0.40	2.12	−0.98	1.15	2.13	−2.11	0.02	2.12	−1.12	0.97	2.09
SEB_75.81	−2.11	0.02	2.13	−1.87	0.25	2.13	3.09	5.08	2.13	7.10	8.97	1.88
SEB_82.88	1.15	3.22	2.07	1.94	3.95	2.02	−0.77	1.33	2.07	20.18	21.52	1.34
SEB_89.95	6.77	8.73	1.96	4.09	6.15	2.06	10.32	12.20	1.96	5.39	7.29	1.90
SEB_96.02	0.15	2.23	2.08	−1.26	0.81	2.07	8.10	9.99	2.08	−1.71	0.39	2.10
SEB_T	−2.11	0.02	2.13	−1.94	0.15	2.09	−2.13	0.002	2.13	−2.12	0.004	2.13
Swedbank_54.60	−1.99	0.14	2.12	−1.59	0.52	2.11	−1.68	0.43	2.12	−2.10	0.02	2.12
Swedbank_61.67	−1.78	0.34	2.12	−1.16	0.90	2.06	−0.94	1.17	2.12	−2.00	0.12	2.12
Swedbank_68.74	−1.79	0.34	2.12	−1.93	0.18	2.11	−1.86	0.25	2.12	−0.88	1.22	2.11
Swedbank_75.81	1.94	3.99	2.05	15.49	17.20	1.71	8.40	10.20	2.05	−1.19	0.90	2.09
Swedbank_82.88	6.96	8.87	1.92	19.96	21.77	1.81	4.14	6.01	1.92	−1.06	1.03	2.09
Swedbank_89.95	−0.42	1.67	2.09	−0.56	1.51	2.07	−1.61	0.51	2.09	−0.59	1.51	2.10
Swedbank_96.02	−2.09	0.04	2.13	−1.83	0.28	2.10	−1.89	0.23	2.13	−2.00	0.12	2.12
Swedbank_T	−2.09	0.04	2.13	−1.98	0.12	2.10	−2.09	0.04	2.13	−2.12	0.003	2.13
SnP500	−2.12	0.01	2.13	−2.10	0.01	2.11	−2.11	0.01	2.13	−2.11	0.01	2.12
Stoxx600	−2.11	0.02	2.13	−2.05	0.06	2.11	−2.11	0.02	2.13	−2.12	0.001	2.12
N100	−2.12	0.01	2.13	−2.08	0.02	2.10	−2.12	0.01	2.13	−2.11	0.005	2.12
N225	−2.13	0.001	2.13	−2.11	0.01	2.11	−2.12	0.004	2.13	−2.13	0.000	2.13
MSCI_world	−2.12	0.01	2.13	−2.02	0.08	2.10	−2.10	0.02	2.13	−2.10	0.02	2.12
EURO_bonds	−2.12	0.004	2.13	−2.05	0.003	2.06	−2.12	0.004	2.13	−2.11	0.000	2.11
FVX	−2.13	0.001	2.13	−2.07	0.002	2.07	−2.13	0.0002	2.13	−2.13	0.001	2.13

The insights from this figure suggest that the overall spillover in financial markets could indicate regime changes and could (together with other methods) be implemented as indicators in automated trading algorithms. However, returns of pension funds should not be considered in such cases as they bring stochasticity to the overall spillover.

Similar results are obtained using VAR spillover (see Fig. 21). However, the overall spillover is less volatile in that case and quite well indicates the beginning of a new global crisis.

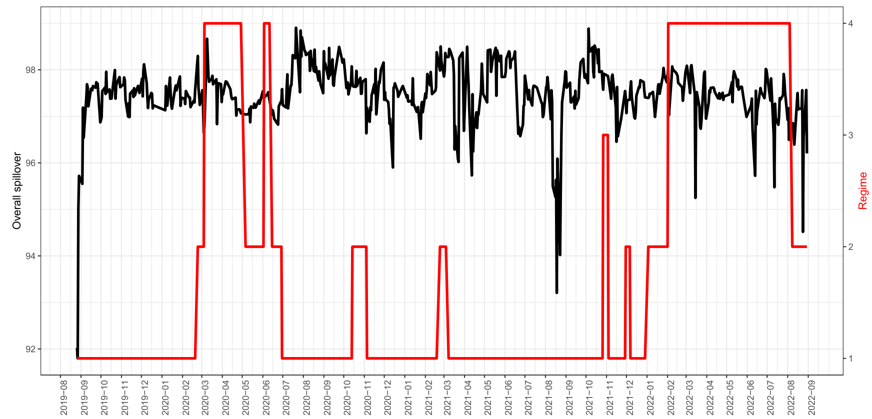

Figure 14 Overall VECM spillover between all data sets analysed using a rolling window of 120 days

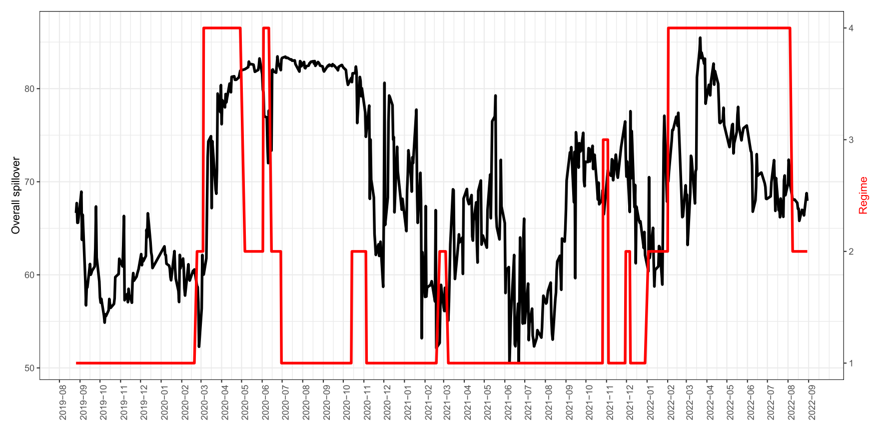

Figure 15 Overall VECM spillover between financial market indices using a rolling window of 120 days

5 Conclusions and discussion

This paper analyses various aspects of connectivity between the second pillar pension funds in Lithuania and takes into account 4 market regimes (no crisis, stress in the stock markets, stress in the bond markets, global financial crisis). Differently, from other similar studies in this article, market regimes are identified using external data sources. Seven well-known financial indices were used for this purpose as pension funds invest in stocks and bonds indices (proportions vary depending on the age of participant). The regimes identified coincide with typical market states described in the media.

The results obtained show that connectedness between pension funds heavily depends on the market regime. Roughly speaking, returns of pension funds are correlated (linearly and non-linearly) quite strongly. However, funds from Allianz manager show the weakest correlation to INVL and Swedbank during global financial crises and periods of no-crisis. During periods of shocks in stock markets, correlations increase. This behaviour indicates a high connectedness between pension funds and financial indices, especially during periods of turmoil. This finding leads to bad news for participants in the pension system and means that during financial crises, independently of the selected pension fund, the funds will behave very similarly. Therefore, supervision authorities, policymakers, and fund management companies should think about a more diverse landscape of pension funds.

The other interesting finding from multivariate or interclass correlation is that the Allianz and Luminor pension funds are more distant from the funds of other managers. While, INVL and Swedbank funds are quite similar to SEB, which behaves more like a group of funds from medium to young age groups. Moreover, these two statements do not depend on the market regime.

The results of Granger causality should be viewed with caution because stationarity cannot be ensured for financial data sets. However, knowing the historical returns of the pension fund and the historical returns of funds from other managers is useful in measuring systemic risk (with some exceptions). Moreover, if financial market data is included in the analysis, then results are quite dependent on the period analysed. Furthermore, results suggest that stock indices are more useful than bond indices in the forecasting of returns of pension funds. This is not a surprise because pension funds mainly invest in stocks rather than bonds (exceptions are preservation funds and funds of the oldest age groups).

Second-pillar pension funds in Lithuania have been analysed using VECM and VAR methods to investigate spillover dynamics between funds over different periods and regimes. According to the results obtained, the transfer of spillover between pension funds is highly dependent on the period and the regime analysed. Net spillover is negative for all Allianz and Luminor funds independently of the regime, and even for some more conservative and stock funds of INVL, SEB, and Swedbank. Throughout the period, the spillover leader is INVL 89–95, but there are some differences during market Regimes 1, 2, and 4. In general, according to the VECM model, Swedbank is the largest spillover generator, leaving INVL in second position. Independently of the method used, Allianz and Luminor funds are spillover absorbers, while Swedbank and INVL are spillover generators. Overall spillover levels do not show a clear relationship with regimes, but lower levels are typically observed during normal regimes in financial markets, while rapid changes are observed more during regimes with shocks. The inclusion of financial market indices into the analysis did not change the structure of the spillover network, and these indices are spillover absorbers independently of the regime. The overall spillover in financial markets could indicate regime changes and could be implemented as indicators in automated trading algorithms, but returns of pension funds should not be considered in such cases, as they bring stochasticity to the overall spillover.

The results of the study are limited to the returns spillover only due to the data collected by the managers of the pension funds. Fund managers collect only daily data as regulation requires. This means that only two observations during the working day are registered: the open and close value of each fund. In case regulation changes or pension fund managers decide to collect more data, this study could be easily extended to volatility spillover analysis (see e.g. [51] how to do that).

Moreover, in this study only the VECM and VAR approaches were used to estimate the spillover. While VECM fits well for the data used and the observed market regimes, the VAR approach was mainly used for the comparison of results. Moreover, the VAR technique requires stationarity of the data, which in this study was achieved by separating the data into 4 regimes. As noted in Sect. 3.4, there exist more econometric models (i.e., BEKK-GARCH or GO-GARCH) to estimate the return spillover and that could be used to confirm the results obtained in this study.

There is a very clear recommendation for shareholders of the pension system (supervisors, policymakers, and fund managers). Pension funds are highly interconnected, suffer from spillover during turmoil periods, and investors (pension system participants) may lose a lot of future benefits if financial crises become more frequent. Therefore, pension fund managers should propose or change existing ones to life-cycle pension funds that are not as heavily interconnected.

Appendix

Table 8 Notations of Lithuanian pension funds, their managers and full original titles in original language

Fund	Manager	Full title of fund
Allianz_54.60	Allianz Lietuva gyvybės draudimas UAB	Allianz B 1954–1960 tikslinės grupės pensijų fondas
Allianz_61.67		Allianz X1 1961–1967 tikslinės grupės pensijų fondas
Allianz_68.74		Allianz X2 1968–1974 tikslinės grupės pensijų fondas
Allianz_75.81		Allianz X3 1975–1981 tikslinės grupės pensijų fondas
Allianz_82.88		Allianz Y1 1982–1988 tikslinės grupės pensijų fondas
Allianz_89.95		Allianz Y2 1989–1995 tikslinės grupės pensijų fondas
Allianz_96.02		Allianz Y3 1996–2002 tikslinės grupės pensijų fondas
Allianz_T		Allianz S turto išsaugojimo pensijų fondas
INVL_54.60	UAB "INVL Asset Management"	INVL pensija 1954–1960 Index Plus
INVL_61.67		INVL pensija 1961–1967 Index Plus
INVL_68.74		INVL pensija 1968–1974 Index Plus
INVL_75.81		INVL pensija 1975–1981 Index Plus
INVL_82.88		INVL pensija 1982–1988 Index Plus
INVL_89.95		INVL pensija 1989–1995 Index Plus
INVL_96.02		INVL pensija 1996–2002 Index Plus
INVL_T		INVL pensijų turto išsaugojimo fondas
Luminor_54.60	Luminor investicijų valdymas UAB	Luminor 1954–1960 tikslinės grupės pensijų fondas
Luminor_61.67		Luminor 1961–1967 tikslinės grupės pensijų fondas
Luminor_68.74		Luminor 1968–1974 tikslinės grupės pensijų fondas
Luminor_75.81		Luminor 1975–1981 tikslinės grupės pensijų fondas
Luminor_82.88		Luminor 1982–1988 tikslinės grupės pensijų fondas
Luminor_89.95		Luminor 1989–1995 tikslinės grupės pensijų fondas
Luminor_96.02		Luminor 1996–2002 tikslinės grupės pensijų fondas
Luminor_T		Luminor turto išsaugojimo fondas
SEB_54.60	UAB "SEB investicijų valdymas"	SEB 1954–1960 metų tikslinės grupės pensijų kaupimo fondas
SEB_61.67		SEB 1961–1967 metų tikslinės grupės pensijų kaupimo fondas
SEB_68.74		SEB 1968–1974 metų tikslinės grupės pensijų kaupimo fondas
SEB_75.81		SEB 1975–1981 metų tikslinės grupės pensijų kaupimo fondas
SEB_82.88		SEB 1982–1988 metų tikslinės grupės pensijų kaupimo fondas
SEB_89.95		SEB 1989–1995 metų tikslinės grupės pensijų kaupimo fondas
SEB_96.02		SEB 1996–2002 metų tikslinės grupės pensijų kaupimo fondas
SEB_T		SEB turto išsaugojimo pensijų kaupimo fondas
Swedbank_54.60	UAB "Swedbank investicijų valdymas"	Swedbank pensija 1954–1960
Swedbank_61.67		Swedbank pensija 1961–1967
Swedbank_68.74		Swedbank pensija 1968–1974
Swedbank_75.81		Swedbank pensija 1975–1981
Swedbank_82.88		Swedbank pensija 1982–1988
Swedbank_89.95		Swedbank pensija 1989–1995
Swedbank_96.02		Swedbank pensija 1996–2002
Swedbank_T		Swedbank turto išsaugojimo pensijų fondas

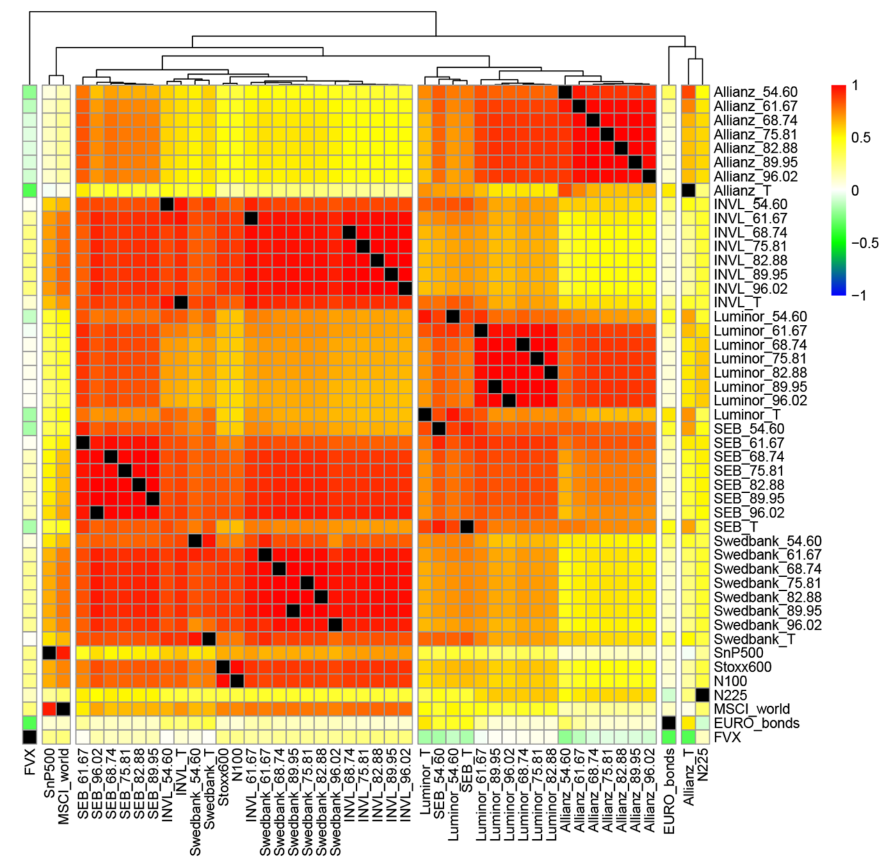

Figure 16 Correlations between all data sets in entire period

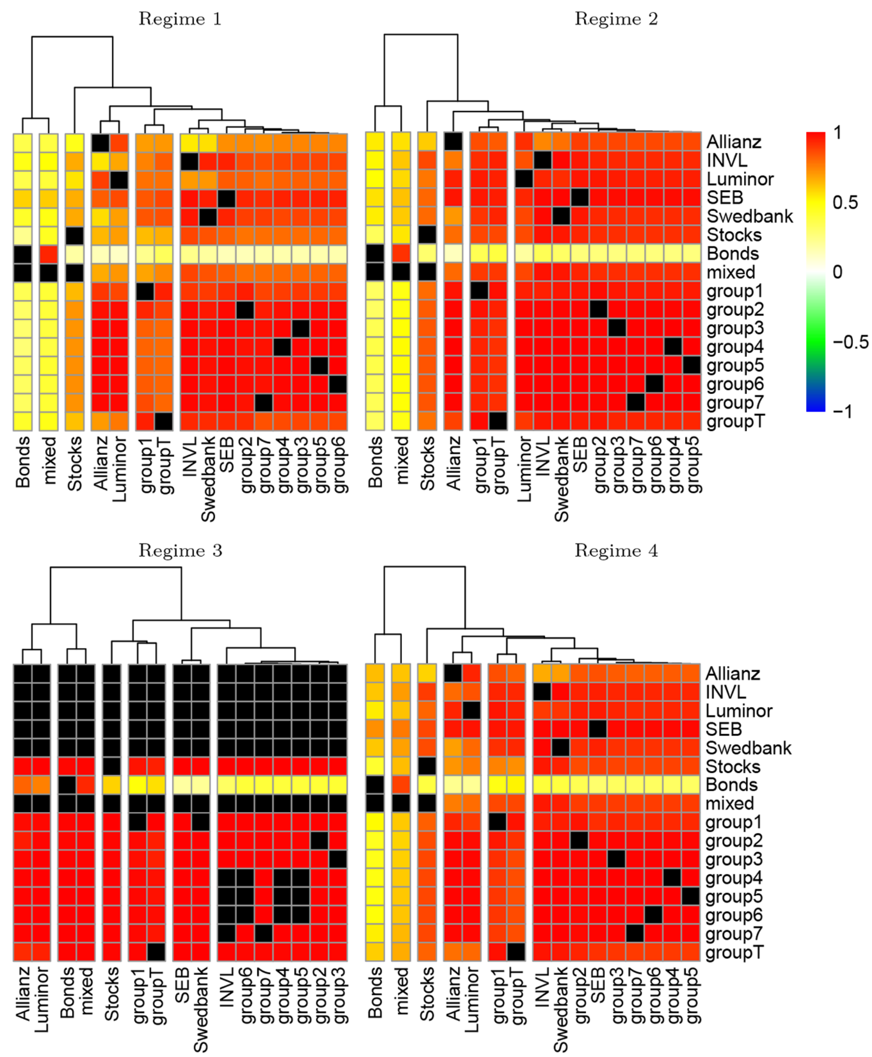

Figure 17 Multivariate correlations in Regimes 1, 2, 3 and 4

Table 9 Multivariate linear correlations between groups of funds

Group	MSCI					EURO bond				
	Full	Regime 1	Regime 2	Regime 3	Regime 4	Full	Regime 1	Regime 2	Regime 3	Regime 4
Allianz	0.218	0.374	0.234	0.676	0.154	0.095	0.093	0.135	0.807	0.136
Invl	0.781	0.743	0.764	0.979	0.810	0.095	0.074	0.179	0.732	0.150
Luminor	0.470	0.539	0.592	0.563	0.398	0.145	0.117	0.139	0.755	0.193
Seb	0.643	0.688	0.621	0.943	0.641	0.121	0.091	0.166	0.747	0.180
Swed	0.747	0.678	0.754	0.888	0.779	0.123	0.073	0.133	0.783	0.187
MSCI 1	1	1	1	1	1	0.140	**0.025**	**0.001**	**0.661**	**0.188**
Bond	0.140	**0.025**	**0.001**	**0.661**	**0.188**	1	1	1	1	1
MSCI and Bond	0.996	0.997	0.999	0.971	0.994	0.172	0.155	**0.093**	0.896	0.218
Age 55–60	0.551	0.489	0.611	0.757	0.565	0.352	0.228	**0.072**	0.933	0.433
Age 61–67	0.637	0.638	0.657	0.867	0.633	0.173	0.082	**0.095**	0.840	0.241
Age 68–74	0.635	0.629	0.651	0.881	0.639	0.103	**0.027**	0.126	0.753	0.162
Age 75–81	0.638	0.642	0.647	0.866	0.637	0.087	**0.023**	0.138	0.710	0.142
Age 82–88	0.640	0.651	0.644	0.865	0.639	0.087	**0.020**	0.140	0.710	0.142
Age 89–95	0.640	0.652	0.644	0.864	0.640	0.087	**0.020**	0.139	0.710	0.142
Age 96–02	0.634	0.621	0.645	0.855	0.641	0.085	**0.017**	0.144	0.716	0.141
Age T	0.584	0.540	0.624	0.724	0.593	0.422	0.321	**0.117**	0.908	0.492

Note: Correlations in bold are not significant.

Table 10 Significance of Granger causality in Regime 1

	Allianz_54.60	Allianz_61.67	Allianz_68.74	Allianz_75.81	Allianz_82.88	Allianz_89.95	Allianz_96.02	Allianz_T	INVL_54.60	INVL_61.67	INVL_68.74	INVL_75.81	INVL_82.88	INVL_89.95	INVL_96.02	INVL_T	Luminor_54.60	Luminor_61.67	Luminor_68.74	Luminor_75.81	Luminor_82.88	Luminor_89.95	Luminor_96.02	Luminor_T	SEB_54.60	SEB_61.67	SEB_68.74	SEB_75.81	SEB_82.88	SEB_89.95	SEB_96.02	SEB_T	Swedbank_54.60	Swedbank_61.67	Swedbank_68.74	Swedbank_75.81	Swedbank_82.88	Swedbank_89.95	Swedbank_96.02	Swedbank_T
Allianz_54.60	*	0	0	0	0	0	0	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Allianz_61.67	0	*	0	0	0	0	0	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Allianz_68.74	0	0	*	0	0	0	0	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	**	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Allianz_75.81	0	0	0	*	0	0	0	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	**	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Allianz_82.88	0	0	0	0	*	0	0	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	**	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Allianz_89.95	0	0	0	0	0	*	0	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	**	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Allianz_96.02	0	0	0	0	0	0	*	0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	**	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Allianz_T	0	0	0	0	0	0	0	*	*	**	***	***	***	***	***	**	**	0	0	0	0	0	0	*	0	0	0	0	0	0	0	**	**	**	**	***	**	**	**	*
INVL_54.60	0	0	0	0	0	0	0	0	*	0	***	***	***	***	***	0	0	0	0	0	0	0	0	0	0	0	0	0	0	***	***	0	*	***	0	0	0	0	**	**
INVL_61.67	0	0	0	0	0	0	0	0	0	*	0	0	***	***	**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	***	0
INVL_68.74	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	***	0
INVL_75.81	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
INVL_82.88	0	0	0	0	0	0	0	0	0	***	0	0	*	0	***	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
INVL_89.95	0	0	0	0	0	0	0	0	0	***	0	0	0	*	**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
INVL_96.02	0	0	0	0	0	0	0	0	0	***	0	0	***	**	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
INVL_T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	***	***	***	0	0	0	0	0	0	0	**	0
Luminor_54.60	0	**	**	**	**	**	**	0	0	0	0	0	0	0	0	0	*	0	0	0	0	***	***	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Luminor_61.67	***	*	*	*	*	*	*	0	*	*	*	*	**	*	**	*	***	*	**	**	**	**	**	0	0	0	0	0	0	0	0	0	***	**	**	**	**	**	**	**
Luminor_68.74	***	*	*	*	*	*	**	0	*	*	*	*	*	*	*	*	***	**	*	0	0	0	0	0	0	0	***	**	**	**	**	0	***	*	*	*	*	*	**	*
Luminor_75.81	***	*	*	*	*	*	*	0	*	*	*	*	*	*	*	*	***	**	0	*	0	0	0	0	0	0	***	**	**	**	**	0	***	*	*	*	*	*	**	*
Luminor_82.88	0	*	*	*	*	*	**	0	*	*	*	*	*	*	*	*	**	**	***	0	*	0	0	0	0	0	**	**	**	**	**	***	***	*	*	*	*	*	**	*
Luminor_89.95	0	**	*	*	*	*	**	0	*	*	*	*	*	*	*	*	**	*	***	***	0	*	0	***	0	***	**	**	*	*	*	**	**	*	*	*	*	*	*	*
Luminor_96.02	0	**	*	*	*	*	**	0	*	*	*	*	*	*	*	*	**	*	***	0	0	0	*	0	0	0	**	**	**	**	*	***	***	*	*	*	*	*	**	*
Luminor_T	***	**	**	**	**	**	**	0	0	0	0	0	0	0	0	0	***	***	***	0	0	***	***	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 10 (*Continued*)

	Allianz_54.60	Allianz_61.67	Allianz_68.74	Allianz_75.81	Allianz_82.88	Allianz_89.95	Allianz_96.02	Allianz_T	INVL_54.60	INVL_61.67	INVL_68.74	INVL_75.81	INVL_82.88	INVL_89.95	INVL_96.02	INVL_T	Luminor_54.60	Luminor_61.67	Luminor_68.74	Luminor_75.81	Luminor_82.88	Luminor_89.95	Luminor_96.02	Luminor_T	SEB_54.60	SEB_61.67	SEB_68.74	SEB_75.81	SEB_82.88	SEB_89.95	SEB_96.02	SEB_T	Swedbank_54.60	Swedbank_61.67	Swedbank_68.74	Swedbank_75.81	Swedbank_82.88	Swedbank_89.95	Swedbank_96.02	Swedbank_T
SEB_54.60	0	0	0	0	0	0	0	0	**	**	**	***	**	**	***	***	**	***	0	0	0	0	0	0	*	0	0	0	0	0	0	**	***	***	0	0	***	***	0	**
SEB_61.67	0	***	***	***	***	0	0	0	0	***	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	***	0	0	0	0	0	0
SEB_68.74	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0
SEB_75.81	0	0	0	0	0	0	0	0	0	**	**	**	**	**	**	0	0	0	0	0	0	0	0	0	0	0	**	*	*	**	**	0	0	***	0	***	***	***	0	0
SEB_82.88	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0
SEB_89.95	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0
SEB_96.02	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0
SEB_T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0
Swedbank_54.60	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0
Swedbank_61.67	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0
Swedbank_68.74	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	***	0	0	0	0
Swedbank_75.81	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	***	*	0	0	0	0
Swedbank_82.88	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0
Swedbank_89.95	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0
Swedbank_96.02	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0
Swedbank_T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	***	0	**	**	**	0	0	0	***	0	0	0	***	*

Note. * - significant with $p < 0.01$, ** - significant with $p < 0.05$, *** - significant with $p < 0.10$, **0** - non-significant with $p > 0.10$.

Table 11 Significance of Granger causality in Regime 2

	Allianz_54.60	Allianz_61.67	Allianz_68.74	Allianz_75.81	Allianz_82.88	Allianz_89.95	Allianz_96.02	Allianz_T	INVL_54.60	INVL_61.67	INVL_68.74	INVL_75.81	INVL_82.88	INVL_89.95	INVL_96.02	INVL_T	Luminor_54.60	Luminor_61.67	Luminor_68.74	Luminor_75.81	Luminor_82.88	Luminor_89.95	Luminor_96.02	Luminor_T	SEB_54.60	SEB_61.67	SEB_68.74	SEB_75.81	SEB_82.88	SEB_89.95	SEB_96.02	SEB_T	Swedbank_54.60	Swedbank_61.67	Swedbank_68.74	Swedbank_75.81	Swedbank_82.88	Swedbank_89.95	Swedbank_96.02	Swedbank_T	SnP500
Allianz_54.60	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Allianz_61.67	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	***
Allianz_68.74	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	***
Allianz_75.81	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	***	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	***
Allianz_82.88	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	***	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	***
Allianz_89.95	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**
Allianz_96.02	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	**	***	***	***	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Allianz_T	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
INVL_54.60	0	0	0	0	0	0	0	0	*	***	***	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**	**	**	**	**	0	0	**	**	**	**	**	**	0	0
INVL_61.67	0	0	0	0	0	0	0	0	***	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	***	0	***	*	*	**	**	**	**	**	0
INVL_68.74	0	0	0	0	0	0	0	0	***	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	***	**	*	*	*	*	***	0
INVL_75.81	0	0	0	0	0	0	0	0	0	0	0	*	0	***	**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**	*	*	**	0	0
INVL_82.88	0	0	0	0	0	0	0	0	0	0	0	0	*	0	**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**	*	*	**	0	0
INVL_89.95	0	0	0	0	0	0	0	0	0	0	0	***	0	*	**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**	**	**	**	0	0
INVL_96.02	0	0	0	0	0	0	0	0	0	0	0	**	**	**	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**	**	**	**	0	0
INVL_T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	***	0	0	0	0	0	0	***	0	0	**	***	***	***	***	0	0	0	**	***	***	***	0	***	0
Luminor_54.60	0	***	***	***	***	***	***	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	***	**	*	*	**	**	**	**	**	0	0	0	0	0	0	0	0	0
Luminor_61.67	0	0	***	***	***	***	**	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Luminor_68.74	***	**	***	**	***	***	**	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Luminor_75.81	***	**	***	***	***	***	**	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Luminor_82.88	0	**	***	***	***	***	**	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Luminor_89.95	0	**	***	***	***	***	**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Luminor_96.02	0	***	0	0	0	0	***	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Luminor_T	0	***	0	***	***	***	***	0	0	0	0	0	0	0	0	0	***	0	0	0	0	0	0	*	*	**	**	**	**	**	**	**	0	0	0	0	0	0	0	0	0

Table 11 (*Continued*)

	Allianz_54.60	Allianz_61.67	Allianz_68.74	Allianz_75.81	Allianz_82.88	Allianz_89.95	Allianz_96.02	Allianz_T	INVL_54.60	INVL_61.67	INVL_68.74	INVL_75.81	INVL_82.88	INVL_89.95	INVL_96.02	INVL_T	Luminor_54.60	Luminor_61.67	Luminor_68.74	Luminor_75.81	Luminor_82.88	Luminor_89.95	Luminor_96.02	Luminor_T	SEB_54.60	SEB_61.67	SEB_68.74	SEB_75.81	SEB_82.88	SEB_89.95	SEB_96.02	SEB_T	Swedbank_54.60	Swedbank_61.67	Swedbank_68.74	Swedbank_75.81	Swedbank_82.88	Swedbank_89.95	Swedbank_96.02	Swedbank_T	SnP500
SEB_54.60	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SEB_61.67	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	***	0
SEB_68.74	0	0	0	0	0	0	0	0	***	0	0	0	0	0	0	***	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	***	0	0	0	0	0	0	**	0
SEB_75.81	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	**	0
SEB_82.88	0	0	0	0	0	0	0	0	***	0	0	0	0	0	0	***	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	**	0
SEB_89.95	0	0	0	0	0	0	0	0	***	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	**	0
SEB_96.02	0	0	0	0	0	0	0	0	***	***	0	0	0	0	0	***	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	***	0	0	0	0	0	0	**	0
SEB_T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0
Swedbank_54.60	0	0	0	0	0	0	0	0	***	0	0	0	0	0	0	0	***	0	0	0	0	0	0	***	0	0	0	0	0	0	***	0	*	***	**	0	0	***	0	**	0
Swedbank_61.67	0	0	0	0	0	0	0	0	**	*	0	0	0	0	0	**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**	*	***	0	0	0	0	**	0
Swedbank_68.74	0	0	0	0	0	0	0	0	*	*	**	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**	0	*	0	0	0	0	**	0
Swedbank_75.81	0	0	0	0	0	0	0	0	**	**	**	**	**	***	***	**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	**	0
Swedbank_82.88	0	0	0	0	0	0	0	0	**	**	*	**	**	**	***	**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	**	0
Swedbank_89.95	0	0	0	0	0	0	0	0	**	**	*	**	**	**	***	**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	***	0	0	0	0	*	0	**	0
Swedbank_96.02	0	0	0	0	0	0	0	0	**	**	*	**	**	***	***	**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**	0
Swedbank_T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**	**	**	**	**	**	0	0	***	***	**	**	**	**	*	0

Note. * - significant with $p < 0.01$, ** - significant with $p < 0.05$, *** - significant with $p < 0.10$, 0 - non-significant with $p > 0.10$.

Table 12 Significance of Granger causality in Regime 4

	Allianz_54.60	Allianz_61.67	Allianz_68.74	Allianz_75.81	Allianz_82.88	Allianz_89.95	Allianz_96.02	Allianz_T	INVL_54.60	INVL_61.67	INVL_68.74	INVL_75.81	INVL_82.88	INVL_89.95	INVL_96.02	INVL_T	Luminor_54.60	Luminor_61.67	Luminor_68.74	Luminor_75.81	Luminor_82.88	Luminor_89.95	Luminor_96.02	Luminor_T	SEB_54.60	SEB_61.67	SEB_68.74	SEB_75.81	SEB_82.88	SEB_89.95	SEB_96.02	SEB_T	Swedbank_54.60	Swedbank_61.67	Swedbank_68.74	Swedbank_75.81	Swedbank_82.88	Swedbank_89.95	Swedbank_96.02	Swedbank_T
Allianz_54.60	*	0	0	0	0	0	0	0	*	*	*	**	**	**	**	*	*	**	0	0	0	0	0	*	*	**	***	0	0	0	***	*	*	*	*	*	*	*	*	*
Allianz_61.67	0	*	0	0	0	0	0	0	*	*	*	*	*	*	*	*	*	*	***	0	0	0	0	*	*	*	*	**	**	**	*	*	*	*	*	*	*	*	*	*
Allianz_68.74	0	0	*	0	0	0	0	0	**	*	**	**	**	**	**	*	*	*	**	0	0	0	0	*	*	*	*	**	*	*	*	**	*	*	*	*	*	*	*	*
Allianz_75.81	0	0	0	*	0	0	0	0	**	*	*	**	**	**	**	*	*	*	**	***	***	***	**	*	*	*	*	*	*	*	*	**	*	*	*	*	*	*	*	*
Allianz_82.88	0	0	0	0	*	0	0	0	**	*	*	**	**	**	**	*	*	*	**	***	***	***	***	*	*	*	*	*	*	*	*	**	*	*	*	*	*	*	*	*
Allianz_89.95	0	0	0	0	0	*	0	0	**	*	*	**	**	**	**	*	*	*	**	***	***	***	***	*	*	*	*	*	*	*	*	**	*	*	*	*	*	*	*	*
Allianz_96.02	0	0	0	0	0	0	*	0	**	*	*	**	**	**	**	*	*	*	*	***	***	***	**	*	*	*	*	*	*	*	*	**	*	*	*	*	*	*	*	*
Allianz_T	0	0	0	0	0	0	0	*	*	**	**	**	**	**	**	*	*	0	0	0	0	0	0	*	**	***	0	0	0	0	0	**	*	**	***	***	***	***	***	*
INVL_54.60	0	0	0	0	0	0	0	***	*	*	*	**	**	**	**	***	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**	**	***	***	***	***	0
INVL_61.67	***	0	0	0	0	0	***	***	*	*	0	0	0	0	0	***	0	0	0	0	0	0	0	0	0	***	0	0	0	0	***	0	0	0	0	0	0	0	0	**
INVL_68.74	***	0	0	0	0	0	***	***	**	0	*	0	0	0	0	***	0	0	0	0	0	0	0	0	0	**	**	***	***	**	**	0	0	0	0	0	***	***	***	**
INVL_75.81	***	0	0	0	0	0	0	***	0	0	0	*	***	0	0	0	0	0	0	0	0	0	0	0	0	***	***	***	***	***	**	0	0	0	0	0	***	***	0	**
INVL_82.88	***	0	0	0	0	0	0	***	0	0	0	***	*	0	0	0	0	0	0	0	0	0	0	0	0	***	***	***	***	***	**	0	0	0	0	0	***	***	0	**
INVL_89.95	***	0	0	0	0	0	0	***	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	***	***	***	***	***	**	0	0	0	0	0	***	***	0	**
INVL_96.02	***	0	0	0	0	0	0	***	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	***	0	***	***	***	***	0	0	0	0	0	0	***	0	**
INVL_T	***	0	0	0	0	0	0	*	0	*	**	**	**	**	***	*	0	0	0	0	0	0	0	**	0	0	0	0	0	0	0	0	0	0	***	0	0	0	0	0
Luminor_54.60	0	0	0	0	0	0	0	**	0	0	0	0	0	0	0	0	*	0	***	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Luminor_61.67	0	0	0	0	0	0	***	0	0	0	0	***	***	***	***	0	0	*	*	**	**	**	0	***	0	0	0	0	0	0	***	0	0	**	**	**	**	**	**	0
Luminor_68.74	0	0	0	0	0	0	0	***	0	0	0	0	0	0	0	0	**	*	*	0	***	0	0	**	0	**	**	**	**	**	**	0	0	**	**	**	*	**	**	0
Luminor_75.81	0	0	0	0	0	0	0	***	0	0	0	0	0	0	0	0	**	**	0	*	0	0	***	**	***	**	**	**	**	**	**	0	0	***	**	**	**	**	**	0
Luminor_82.88	0	0	0	0	0	0	0	***	0	0	0	0	0	0	0	0	**	*	***	0	*	***	**	**	***	**	**	**	**	**	**	0	0	***	**	**	**	**	**	0
Luminor_89.95	0	0	0	0	0	0	0	***	0	0	0	0	0	0	0	0	**	*	0	0	0	*	***	**	0	**	**	**	**	**	**	0	0	***	**	**	**	**	**	0
Luminor_96.02	0	0	0	0	0	0	0	***	0	0	0	0	0	0	0	0	**	**	0	0	0	0	*	**	0	***	***	***	***	***	***	0	0	0	***	**	**	**	**	0
Luminor_T	0	0	0	0	0	0	0	**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 12 (*Continued*)

	Allianz_54.60	Allianz_61.67	Allianz_68.74	Allianz_75.81	Allianz_82.88	Allianz_89.95	Allianz_96.02	Allianz_T	INVL_54.60	INVL_61.67	INVL_68.74	INVL_75.81	INVL_82.88	INVL_89.95	INVL_96.02	INVL_T	Luminor_54.60	Luminor_61.67	Luminor_68.74	Luminor_75.81
SEB_54.60	**	**	***	0	0	0	***	**	0	0	0	0	0	0	0	0	0	0	0	0
SEB_61.67	**	***	***	***	***	0	**	**	0	0	0	0	0	0	0	0	0	0	0	***
SEB_68.74	**	***	0	0	0	0	***	*	0	0	0	0	0	0	0	0	***	**	***	***
SEB_75.81	**	0	0	0	0	0	***	*	0	0	0	0	0	0	0	0	***	**	***	0
SEB_82.88	**	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	***	**	***	0
SEB_89.95	**	0	0	0	0	0	0	*	0	0	0	0	0	0	0	0	***	**	0	0
SEB_96.02	**	***	0	0	0	0	0	*	0	0	0	0	0	0	0	0	***	**	0	0
SEB_T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Swedbank_54.60	0	0	0	0	0	0	0	**	0	***	**	***	***	***	***	0	0	0	0	0
Swedbank_61.67	**	0	0	0	0	0	0	*	0	0	***	0	0	0	0	0	0	0	0	0
Swedbank_68.74	**	***	0	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0
Swedbank_75.81	**	***	0	0	0	0	0	*	0	0	***	0	0	0	0	0	0	0	0	0
Swedbank_82.88	**	0	0	0	0	0	0	*	0	0	***	***	0	0	0	0	0	0	0	0
Swedbank_89.95	**	0	0	0	0	0	0	*	0	0	***	***	***	***	0	0	0	0	0	0
Swedbank_96.02	**	0	0	0	0	0	0	*	0	0	***	0	0	0	0	0	0	0	0	0
Swedbank_T	0	0	0	0	0	0	0	**	0	**	*	*	*	*	*	0	0	0	0	0

	Luminor_82.88	Luminor_89.95	Luminor_96.02	Luminor_T	SEB_54.60	SEB_61.67	SEB_68.74	SEB_75.81	SEB_82.88	SEB_89.95	SEB_96.02	SEB_T	Swedbank_54.60	Swedbank_61.67	Swedbank_68.74	Swedbank_75.81	Swedbank_82.88	Swedbank_89.95	Swedbank_96.02	Swedbank_T
SEB_54.60	0	0	0	0	*	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SEB_61.67	***	***	0	0	0	*	**	**	**	**	**	0	0	0	**	**	**	**	**	0
SEB_68.74	***	***	***	***	***	**	*	0	0	0	0	0	0	0	***	***	***	***	***	0
SEB_75.81	0	0	0	***	***	**	0	*	0	0	0	0	0	0	0	0	***	0	0	0
SEB_82.88	0	0	0	***	***	***	0	0	*	0	0	0	0	0	0	0	***	0	0	0
SEB_89.95	0	0	0	***	0	***	0	0	0	*	0	0	0	0	0	***	***	0	0	0
SEB_96.02	0	0	0	***	0	***	0	0	0	0	*	0	0	0	0	***	***	***	0	0
SEB_T	0	0	0	0	0	0	0	0	0	0	0	*	0	0	0	0	0	0	0	***
Swedbank_54.60	0	0	0	0	0	0	0	0	0	0	0	0	*	**	**	**	**	**	**	**
Swedbank_61.67	0	0	0	***	0	0	0	0	0	0	0	0	***	*	***	**	***	***	0	*
Swedbank_68.74	0	0	0	0	0	***	0	0	0	0	0	0	***	0	*	0	0	0	0	**
Swedbank_75.81	0	0	0	0	0	0	0	0	0	0	0	0	***	**	0	*	0	0	0	**
Swedbank_82.88	0	0	0	0	0	0	0	0	0	0	0	0	***	***	0	0	*	0	0	**
Swedbank_89.95	0	0	0	0	0	0	0	0	0	0	0	0	***	0	0	0	0	*	0	**
Swedbank_96.02	0	0	0	0	0	0	0	0	0	0	0	0	***	0	0	0	0	0	*	**
Swedbank_T	0	0	0	0	0	0	0	0	0	0	***	0	0	*	*	*	*	*	*	*

Note. * - significant with $p < 0.01$, ** - significant with $p < 0.05$, *** - significant with $p < 0.10$, **0** - non-significant with $p > 0.10$.

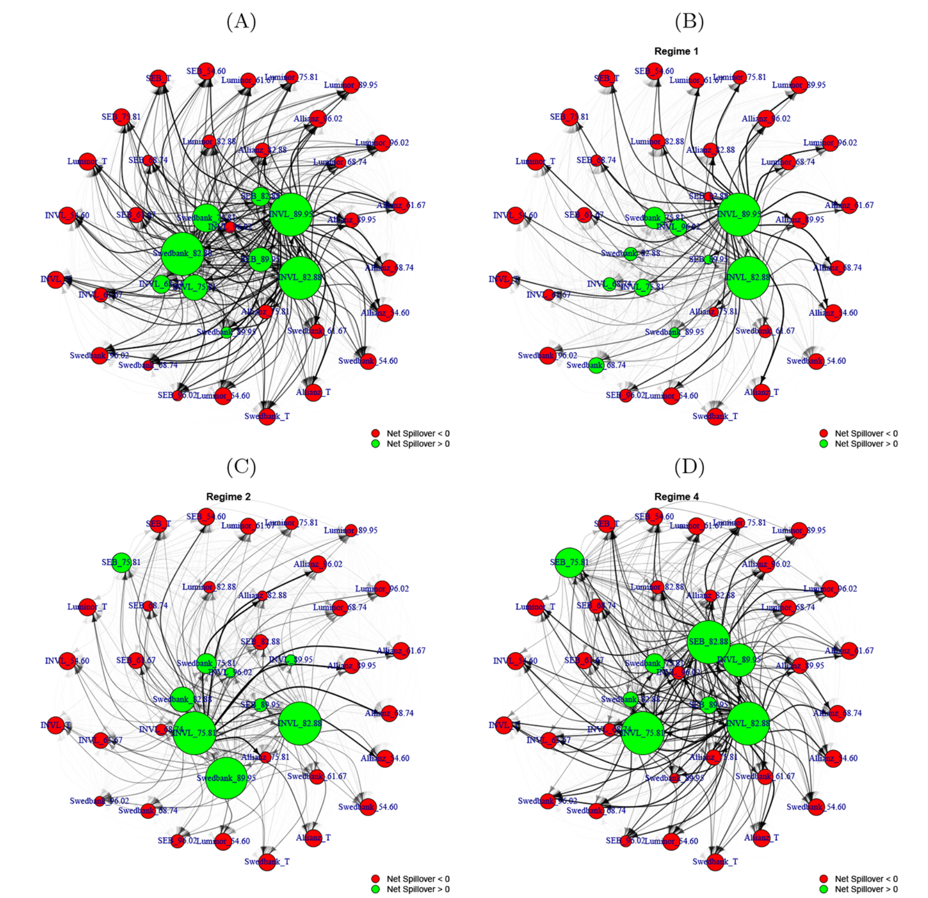

Figure 18 Spillover networks in different regimes (entire period (A), no crisis (B), stock crisis (C), global financial crisis(D)) using VAR models

Table 13 Spillover (net, from and to) using VAR model

Fund	Entire period			Regime 1			Regime 2			Regime 4		
	Net	From	To	Net	From	To	Net	From	To	Net	From	To
Allianz_54.60	−2.45	0.05	2.50	−2.46	0.04	2.50	−2.47	0.03	2.50	−2.49	0.01	2.50
Allianz_61.67	−2.25	0.25	2.49	−2.23	0.26	2.49	−2.42	0.08	2.50	−2.43	0.07	2.50
Allianz_68.74	−2.14	0.35	2.49	−1.79	0.70	2.49	−2.18	0.31	2.49	−2.30	0.19	2.50
Allianz_75.81	−1.61	0.86	2.48	−0.28	2.18	2.46	−0.74	1.72	2.46	−1.97	0.52	2.49
Allianz_82.88	−1.78	0.70	2.48	−1.75	0.74	2.49	−0.39	2.06	2.45	−1.01	1.44	2.45
Allianz_89.95	−1.76	0.72	2.48	−2.24	0.26	2.49	−2.08	0.42	2.49	−2.02	0.46	2.48
Allianz_96.02	−2.43	0.06	2.50	−2.47	0.03	2.50	−2.43	0.06	2.50	−2.48	0.02	2.50
Allianz_T	−2.48	0.01	2.50	−2.49	0.01	2.50	−2.50	0.005	2.50	−2.50	0.00	2.50
INVL_54.60	−2.45	0.05	2.50	−2.43	0.06	2.49	−2.45	0.05	2.50	−2.47	0.03	2.50
INVL_61.67	−1.66	0.81	2.47	−0.78	1.64	2.42	−2.07	0.42	2.49	−2.21	0.29	2.49
INVL_68.74	2.79	5.14	2.35	1.35	3.68	2.33	−0.82	1.64	2.45	−1.27	1.20	2.48
INVL_75.81	4.95	7.24	2.28	2.45	4.77	2.32	19.88	21.87	1.99	11.62	13.60	1.98
INVL_82.88	11.88	13.97	2.10	16.21	18.33	2.12	14.19	16.32	2.13	16.09	18.02	1.93
INVL_89.95	13.79	15.87	2.08	27.34	29.23	1.89	0.69	3.10	2.41	7.08	9.44	2.36
INVL_96.02	−0.77	1.69	2.46	2.53	4.83	2.31	0.47	2.86	2.39	−1.31	1.17	2.48
INVL_T	−2.47	0.02	2.50	−2.47	0.02	2.49	−2.49	0.01	2.50	−2.49	0.01	2.50
Luminor_54.60	−2.45	0.05	2.50	−2.41	0.08	2.49	−2.47	0.03	2.50	−2.49	0.01	2.50
Luminor_61.67	−1.92	0.56	2.48	−1.91	0.58	2.49	−2.19	0.30	2.50	−2.40	0.10	2.50
Luminor_68.74	−0.91	1.54	2.45	−1.88	0.61	2.49	−2.10	0.38	2.48	−2.14	0.35	2.49
Luminor_75.81	−1.26	1.21	2.47	−1.46	1.03	2.49	−1.36	1.09	2.45	−0.44	2.01	2.46
Luminor_82.88	−1.42	1.05	2.47	−1.91	0.59	2.49	−0.90	1.53	2.42	−1.32	1.15	2.47
Luminor_89.95	−2.37	0.13	2.50	−2.47	0.02	2.50	−1.05	1.39	2.44	−2.21	0.28	2.49
Luminor_96.02	−2.28	0.22	2.49	−2.16	0.33	2.49	−2.14	0.35	2.49	−2.45	0.05	2.50
Luminor_T	−2.47	0.03	2.50	−2.47	0.02	2.49	−2.49	0.01	2.50	−2.49	0.01	2.50
SEB_54.60	−2.42	0.07	2.50	−2.37	0.13	2.49	−2.45	0.04	2.50	−2.46	0.04	2.50
SEB_61.67	−1.98	0.50	2.48	−1.91	0.58	2.48	−2.11	0.38	2.49	−2.24	0.25	2.49
SEB_68.74	−0.69	1.77	2.45	−0.81	1.65	2.46	−0.51	1.96	2.46	−1.78	0.70	2.48
SEB_75.81	−2.45	0.04	2.50	−2.47	0.02	2.49	3.22	5.62	2.40	6.10	8.39	2.29
SEB_82.88	3.01	5.37	2.36	−0.11	2.37	2.48	−1.92	0.56	2.48	15.19	17.26	2.07
SEB_89.95	4.52	6.83	2.31	0.12	2.57	2.46	1.32	3.76	2.44	2.45	4.85	2.41
SEB_96.02	−0.52	1.93	2.45	−1.25	1.21	2.46	−1.43	1.06	2.48	−0.79	1.67	2.46
SEB_T	−2.48	0.02	2.50	−2.43	0.06	2.49	−2.49	0.01	2.50	−2.50	0.00	2.50
Swedbank_54.60	−2.14	0.35	2.49	−2.10	0.35	2.46	−2.39	0.11	2.50	−2.33	0.16	2.50
Swedbank_61.67	−1.68	0.80	2.48	−1.26	1.20	2.46	−1.77	0.72	2.49	−1.99	0.50	2.49
Swedbank_68.74	−0.41	2.05	2.46	2.05	4.42	2.37	−1.79	0.69	2.48	−1.99	0.50	2.49
Swedbank_75.81	5.68	8.00	2.32	3.73	6.02	2.29	3.30	5.60	2.31	3.25	5.62	2.37
Swedbank_82.88	11.36	13.55	2.19	1.35	3.82	2.47	4.75	7.04	2.28	1.95	4.36	2.40
Swedbank_89.95	0.81	3.25	2.44	0.48	2.94	2.46	9.59	11.76	2.16	−0.36	2.09	2.45
Swedbank_96.02	−2.34	0.16	2.50	−2.43	0.06	2.49	−0.38	2.06	2.44	−1.92	0.56	2.49
Swedbank_T	−2.35	0.15	2.50	−2.40	0.08	2.48	−2.45	0.04	2.50	−2.48	0.02	2.50

Note: The cross correlation elements in this table are not set to 0.

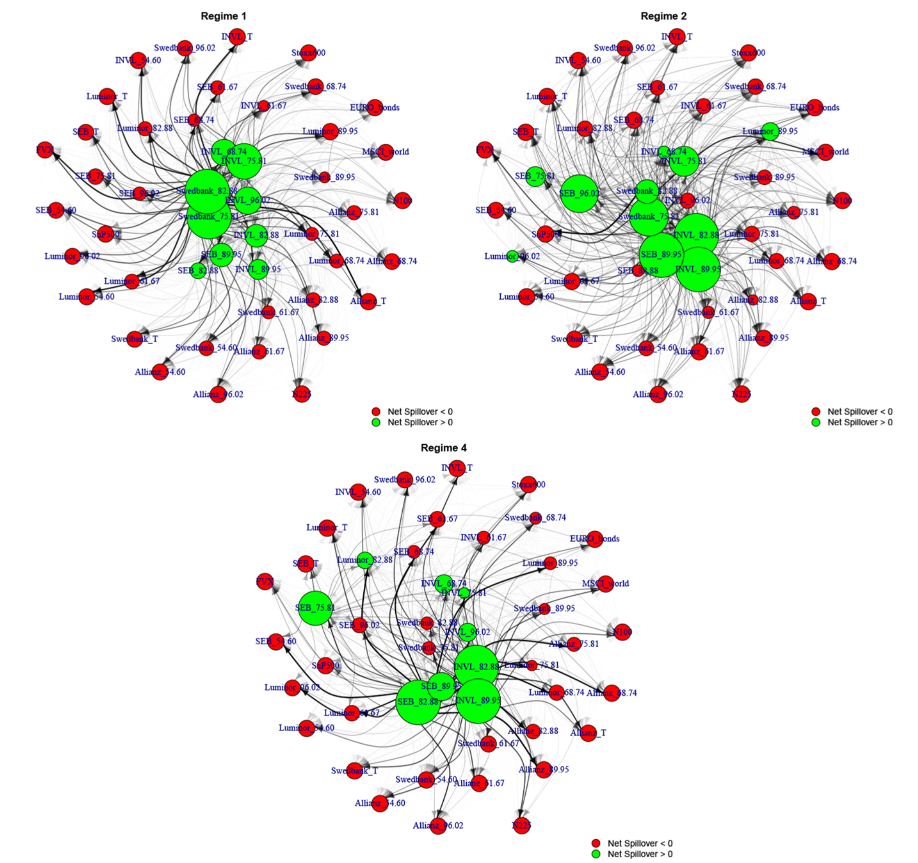

Figure 19 Spillover networks in different regimes (no crisis, stock crisis, global financial crisis) using VECM models (including market indices)

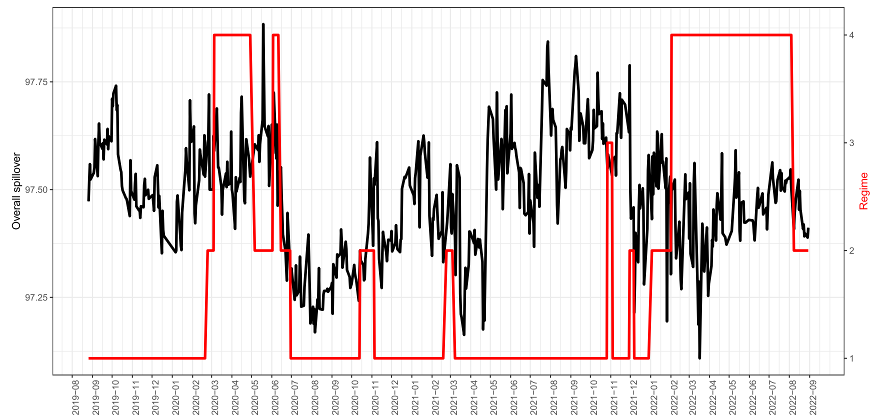

Figure 20 Overall VAR spillover between pension funds using rolling window of 120 days

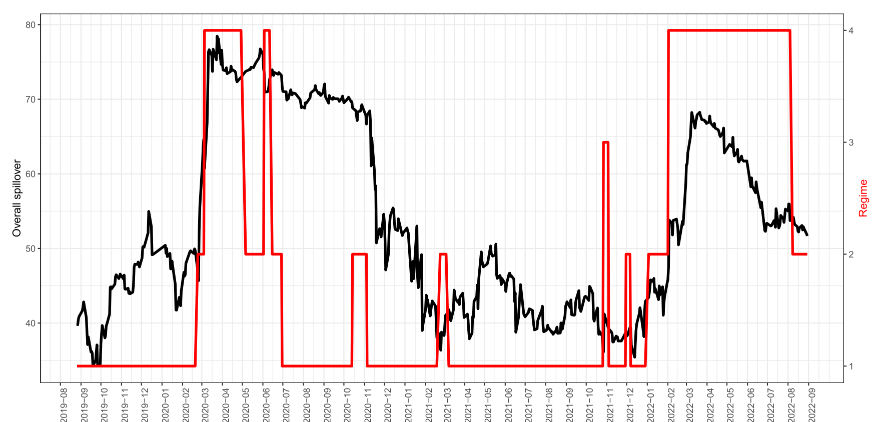

Figure 21 Overall VAR spillover between financial market indices using rolling window of 120 days

Author contributions
The author read and approved the final manuscript.

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Data availability
The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
This article does not contain any studies with human participants or animals performed by any of the authors.

Competing interests
The author declares no competing interests.

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