Methods for Evaluation of Concentration and Interconnectedness in Holdings of Institutional Investors

Ariel Mantzura and Ohad Zada

Summary

The Bank of Israel, as part of its function, evaluates the robustness, efficiency, and stability of the financial system. This evaluation is conducted by monitoring activity in the financial system, and one of the challenges faced is the concise presentation of system data, which is also designed to indicate any potential vulnerabilities therein. In this document we present examples of commonly used methods for empirical analysis of assets held by institutional investors. Empirical analysis may point to vulnerabilities in the financial system, and particularly to those resulting from the extent of concentration and interconnectedness therein, which, in case of a shock to the system, may result in the materialization of system-wide contagion risk.

1. Introduction and literature overview

One of the challenges in monitoring a financial system lies in the concise presentation of system data in order to examine its robustness, efficiency, and stability and to further point to any potential vulnerabilities therein. Information is often presented through constructed benchmarks that summarize data, visualization methods and modeling by means of a network graph. This method has become commonplace in recent years (Poledna et.al 2021), and allows for mapping of the relationships between participants and their strength, specifying clusters of participants, and ranking participants by their importance and centrality in the system.

The objective of this document is to present an overview and examples of commonly used methods for the empirical analysis of assets held by institutional investors at the management company level, particularly pension funds, insurance companies[1], and provident funds. Empirical analysis may point to vulnerabilities in the financial system, and particularly to those resulting from the extent of concentration and interconnectedness therein, which, in case of a shock to the system, may result in the materialization of system-wide contagion risk.

In this document we used a specific database, based on quarterly reports published by institutional investors pursuant to reporting directives of the Capital Market, Insurance and Savings Authority, including details of their holdings by management company, track, and individual asset. Such detailed information allows us to analyze the extent of similarity and correlation in the holdings of market participants. This document is focused on holdings of equities and corporate bonds in Israel, which are deemed negotiable assets that may be quickly liquidated (see Barruca 2021), from 2011 to date.

High concentration in the institutional market affects competition, the performance of management companies, consumer well-being, efficient capital allocation, asset pricing, and so forth.[2] The Israeli Securities Authority (2020)[3], in a comprehensive report, points to the high concentration existing in the institutional market in Israel, by calculating commonly-used benchmarks for concentration (such as Herfindahl-Hirschman Index, CR3 etc.) The report statistically reviewed the effect of concentration on the volatility and liquidity of the assets held by institutional investors. The authors find that an increase in institutional investors' holdings and high concentration are correlated with lower liquidity of the assets in which they invest. In this document, we present and provide more information about another concentration benchmark, known as the effective number, and compare it to the Herfindahl-Hirschman Index (Herfindahl, 1959; Hirschman, 1945), which is considered a commonplace benchmark for concentration (see Barruca 2021).

Strong interconnectedness in the financial system may result in the materialization of systemic risk, where an external shock, insolvency, or liquidity issues in one company or in multiple companies affect other companies in the system, through some contagion

1 This document only includes information with regard to profit-sharing insurance policies.

2 See box in the *Financial Stability Report* for the second half of 2022.

3 Developments in Management of Public Funds in Israel over the Past Decade and Its Implications on the Capital Market (2020).

mechanism. The literature describes several commonplace contagion mechanisms in the financial system. Poledna (2021) distinguishes between direct contagion and indirect contagion. Direct contagion (Upper et al. 2002) results from direct exposures between two companies, through loans between the parties. The exposure is reflected and measured under liabilities on the companies' balance sheets. Indirect contagion occurs when financial companies hold similar assets. This contagion mechanism is referred to in the literature as Overlapping Portfolios (Levy-Carciente et al. 2015). It typically involves the following: Due to an external shock to the company or to one or more assets held by it, the company is required to liquidate assets at far below market prices (fire sale). A fire sale drives asset prices down, resulting in losses for other companies holding the same assets. Elsinger et al. (2006) reviewed systemic risk in the Austrian banking system, and found that direct contagion risk is the primary source of systemic risk. (Barucca et al. 2021) reviewed the extent of systemic interconnectedness and vulnerability due to indirect contagion, across different types of financial institutions. (Kosenko et al. 2022) analyze another contagion mechanism of overlapping portfolios in the nontradable loan portfolio among banks, and find that this contagion mechanism significantly contributes to systemic risk.

Section 2 describes the database used in this document. Sections 3 and 4 provide more information about concentration and similarity benchmarks. Section 5 shows how visual presentation may be used to describe the financial system. Section 6 concludes.

2. Database description

In this document, we used a specific database created by Praedicta.[4] The database includes data on institutional investors' holdings in equities and corporate bonds in Israel by management company, since 2010. This is quarterly data by product type, track, and individual asset, so for each management company and product type, and for each track, it provides details of each individual asset holding. The table below shows examples of typical records within the database.

Table 1: Examples of typical database records

Management company	Product type	Track name	Type of securities	Number of securities	(Short) name of securities	Market cap
Company A Provident and Pension Funds Ltd.	Pension fund	Target retirement 2040	Tradable corporate bonds	11111	Bond A	500,855
Company A Provident and	Provident funds	Target retirement 2040	Equities – Tel Aviv 35	22222	Equity A	12,955,137

[4] Praedicta is a fintech company specializing in processing financial information to create significant tools to help in decision-making and setting strategy for investment management. Since the 1980s, they have been collating financial and economic information of all types, cataloging it, and storing it in enormous data warehouses (taken from the company website).

Pension Funds Ltd.						
Company B Provident and Pension Funds Ltd.	Provident funds	Bonds track, up to 25% equity	Tradable corporate bonds	3333	Bond B	7,920,403
Company B Provident and Pension Funds Ltd.	Provident funds	Bonds track, up to 25% equity	Equities – Tel Aviv 35	4444	Equity B	3,410,613

3. Concentration benchmarks

In this document we review multiple concentration benchmarks at the management company level by product type: Insurance companies, pension funds, and provident funds. We review concentration in three dimensions:

a. Management company concentration;
b. Track concentration;
c. Asset concentration.

By reviewing these benchmarks by trading location, we can find out how many management companies, tracks, and assets effectively exist. The absolute number of companies is simply a count of all companies, regardless of the extent of their assets, while the effective number would be less than or equal to this number, because companies with lower asset holdings would be assigned only a partial weight in the count. For example, let us assume 3 companies with asset holdings as listed in the table below:

Company A	Company B	Company C
10000	10	5

Thus, the absolute number of companies is 3, with each company counted once, regardless of the extent of their asset holdings, but the effective number is close to 1 (depending on the calculation method), since the vast majority of assets are held by only one company.
For this purpose, we use the Herfindahl-Hirschman Index and entropy.[5] These benchmarks are calculated quarterly, so we may review their evolution over time.

Herfindahl-Hirschman Index

We assume that the overall portfolio of management companies is invested in k assets, with distribution across various assets represented by the following series (vector):

$$v = (v_1, v_2, \dots, v_k)$$

[5] Entropy is a scientific term, typically identified with a chaotic, disordered, and random situation.

where v_i is the monetary value of holdings in asset *i*. Let $p = p_1, \dots, p_n$ be the series of numbers representing the weight of holdings in various assets, where $p_i = \frac{v_i}{\sum_{\{j=1\}}^{k} v_J}$ is the weight (ratio) of holdings in asset *i*. The Herfindahl-Hirschman Index is defined as the sum of squares of the weight series.

$$HHI = ||p||^2 = \sum_{\{i=1\}}^{k} p_i^2$$

The Herfindahl-Hirschman Index equals 1 with full concentration, or $\frac{1}{k}$ with maximum diversification.

Entropy

The second benchmark we used is based on entropy, and is defined as follows:

$$EFF = 2^{H(p)}$$

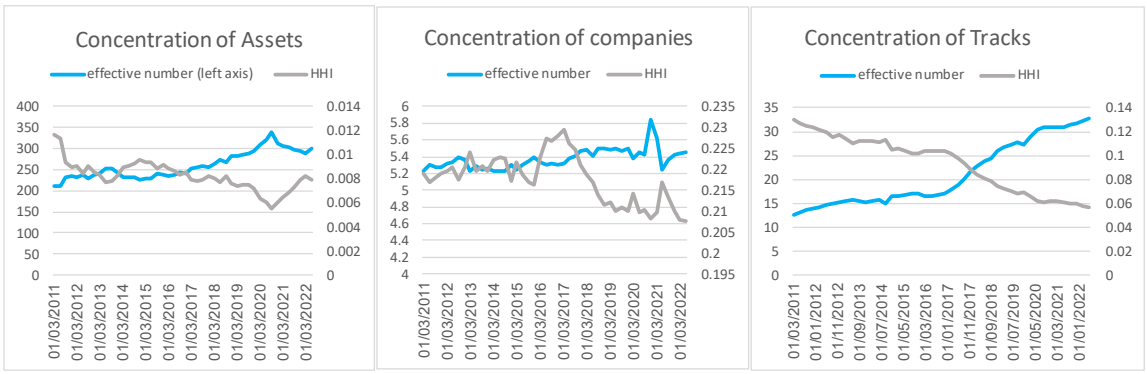
where:

$$H(p) = -\sum_{\{i=1\}}^{k} p_i log_2(p_i)$$

Entropy *H(p)* is a common measure of diversification, with values ranging from 0 to $\log_2 k$, where 0 indicates full concentration and $\log_2 k$ reflects full, uniform diversification, in a case where $p_1 = p_2 = \cdots = p_k = \frac{1}{k}$.

These benchmarks often mirror each other, as shown in Diagram 1 below.

Diagram 1: Typical Herfindahl-Hirschman Index vs. effective number in insurance companies



Nevertheless, the EFF benchmark, with values between 1 and *k*[6] is sometimes preferred for its intuitive interpretation for the effective number, whereas the Herfindahl-Hirschman Index ranges between $\frac{1}{k}$ and 1.

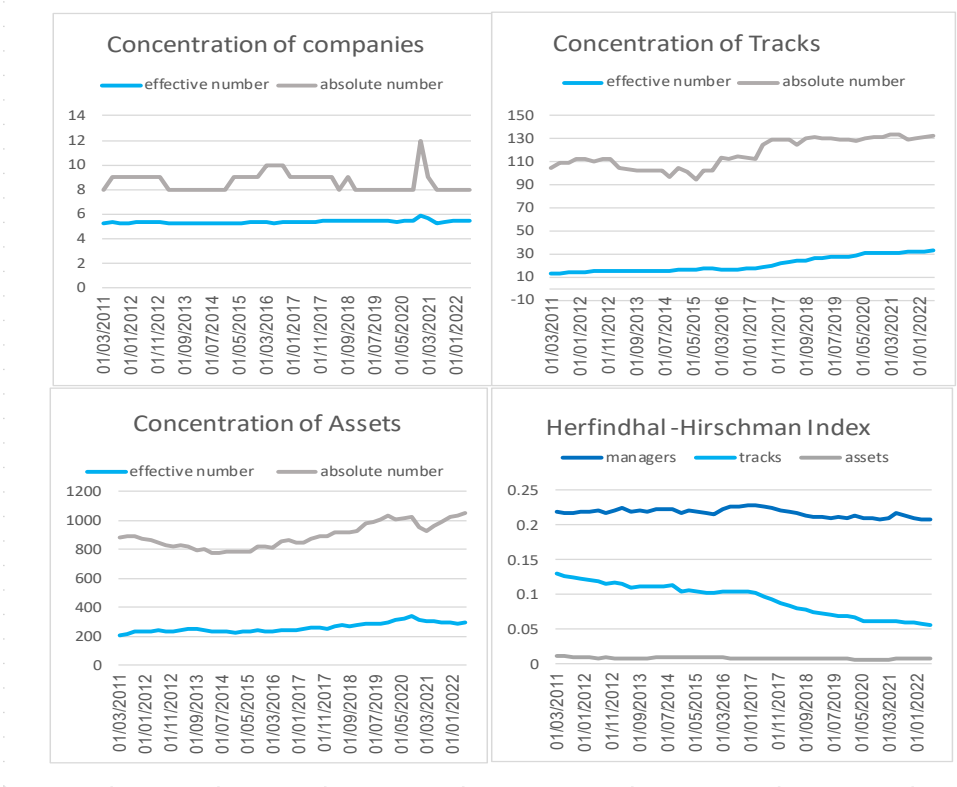
These two benchmarks are calculated in the same way for management companies, tracks, and assets. For example, when calculating concentration for management companies, *k*

[6] $2^0 = 1, 2^{\log_2 k} = k$

would indicate the number of management companies, and $v_1, \ldots, v_k$ would be a series of all assets held by each management company.

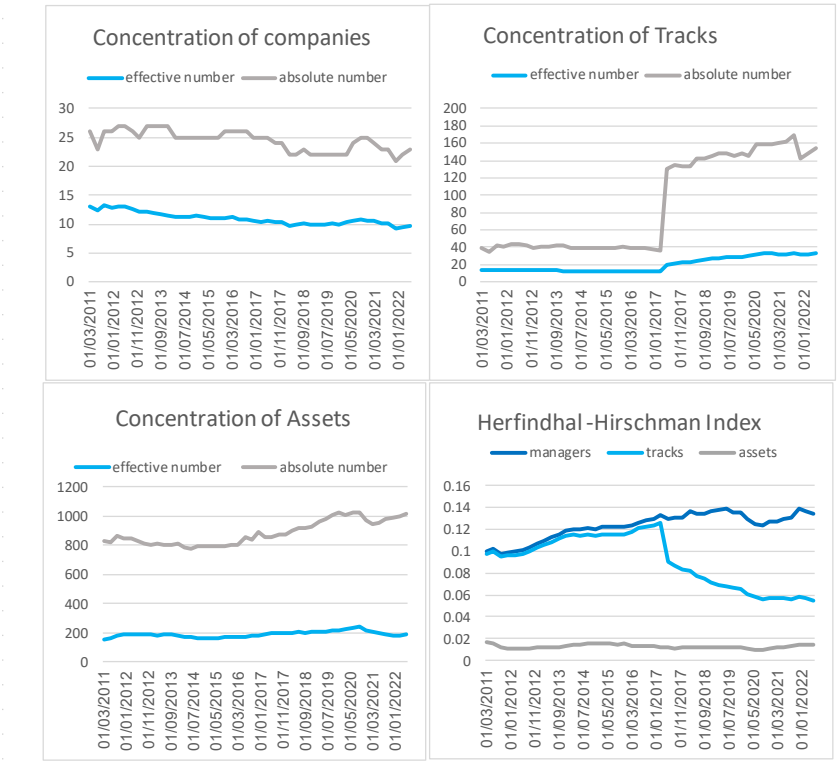
Diagrams 2-4 below show the concentration benchmarks by product type.

Diagram 2: Concentration benchmarks with regard to insurance companies



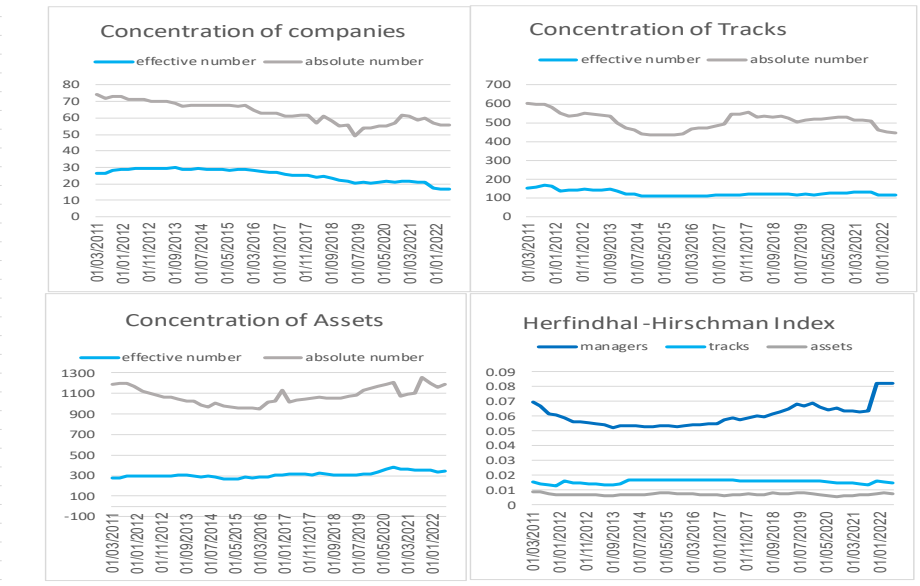
The concentration benchmarks with regard to insurance companies show that the effective number of companies, tracks, and assets is significantly smaller than their absolute number. This indicated higher concentration than reflected by the absolute number, i.e. a higher percentage of capital is held by fewer companies, in fewer tracks, and in fewer assets than indicated by the absolute number. We can also see slight improvement over time in the effective number of assets and tracks, with practically no change in the effective number of companies.

Diagram 3: Concentration benchmarks with regard to pension funds



With regard to pension funds, we can see a slight improvement in capital diversification across a larger number of assets. The effective number of management companies indicates higher concentration compared with their absolute number. Around 2017, one can see a structural rift in track concentration. This rift is technical, caused by a change to reporting directives, which also required pension funds to provide detailed reporting by track, as opposed to the previous period – where they only reported at company level.

Diagram 4: Concentration benchmarks with regard to provident funds



Provident funds show a decrease in the absolute number of companies, as well as a more

moderate decline in the effective number of companies. An increase in the effective number of assets is also evident.

4. Similarity benchmarks

This section describes how we examine the similarity of portfolios of each pair of management companies, using a benchmark called "cosine similarity". For example, Girardi Girardi et al. (2021) examine the indirect contagion channel in the insurance sector using this benchmark, as described below. For each company, we added up the holdings in each asset across all tracks for the company. Next, we calculated the cosine similarity benchmark for each company pair. When holdings do not take negative values, this benchmark has a value between 0 and 1, where 0 indicates absolute dissimilarity and 1 indicates complete similarity of portfolios for the two companies. In each quarter, we represent the calculated benchmarks by means of matrix, where cell(i,j) shows the cosine similarity benchmark for companies *i and j*. As we show below, these matrices may be created as a heat map, such that companies with greater similarity are closer together in the matrix. Below is a formal definition of cosine similarity.

Cosine similarity

We assume 2 management companies with holdings in assets 1,...,k represented by these two vectors:

$$w = (w_1, \dots, w_k)$$

$$v = (v_1, \dots, v_k)$$

Where $w_i, v_i > 0$ is each company's total holding of asset *i*. The cosine similarity benchmark between these two vectors is defined as:

$$Cos(v,w) = \frac{\sum_{\{i=1\}}^{k} w_i v_i}{\sqrt{\sum_{\{i=1\}}^{k} {v_i}^2}\ \sqrt{\sum_{\{i=1\}}^{k} w_i^2}}$$

This benchmark may, in general, take negative values—but in our case, there generally are no negative holdings in assets, which would give it values between 0 and 1. Diagram 5 shows an example heat map, calculated based on the effective number of management companies for each savings sector, in the third quarter of 2022.

Diagram 5 – Heat maps of cosine similarity by type of institutional investor – Israel

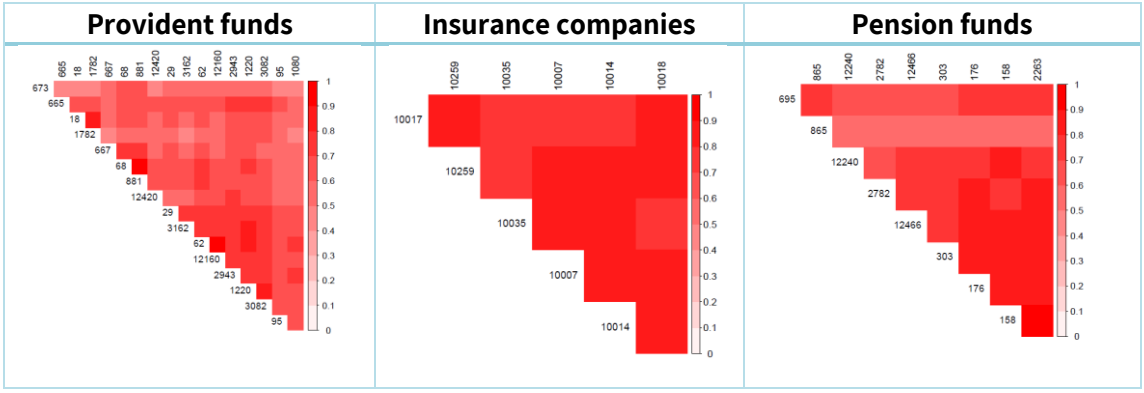
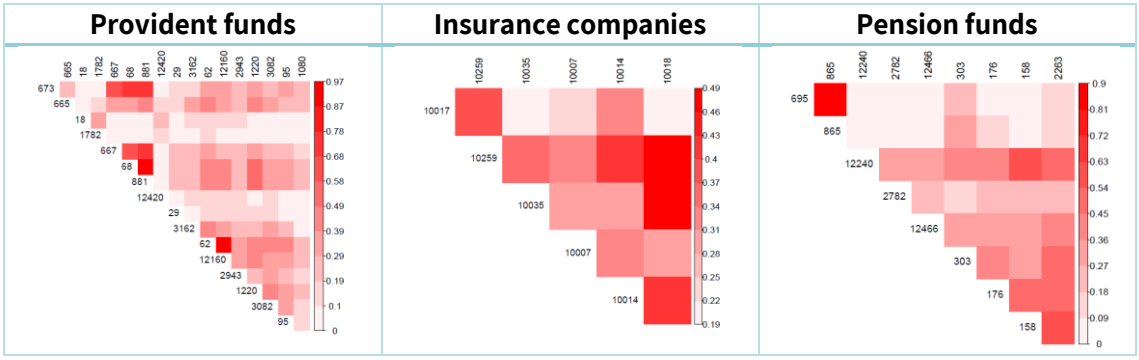


Diagram 5 shows that the heat map for the second quarter of 2022 indicates the strong similarity between companies across all product types. However, the highest similarity appears to be among insurance companies, and the lowest similarity – among provident funds. For comparison, Diagram 6 below contains heat maps for overseas holdings of these management companies, and shows that there is significantly less similarity between the companies, as reflected by the color of these heat maps.

Diagram 6 – Heat maps of cosine similarity by type of institutional investor – overseas



The heat maps show the state of affairs in a given quarter. We wish to see the evolution of similarity over time. To this end, we should add up the information in the heat map for each quarter. We do this by calculating the average and standard deviation for the similarity benchmark for each quarter. Diagram 7 below shows the average cosine similarity benchmark over time, ± one standard deviation, for each product type.

Diagram 7 – Average cosine similarity over time by type of institutional investor – Israel

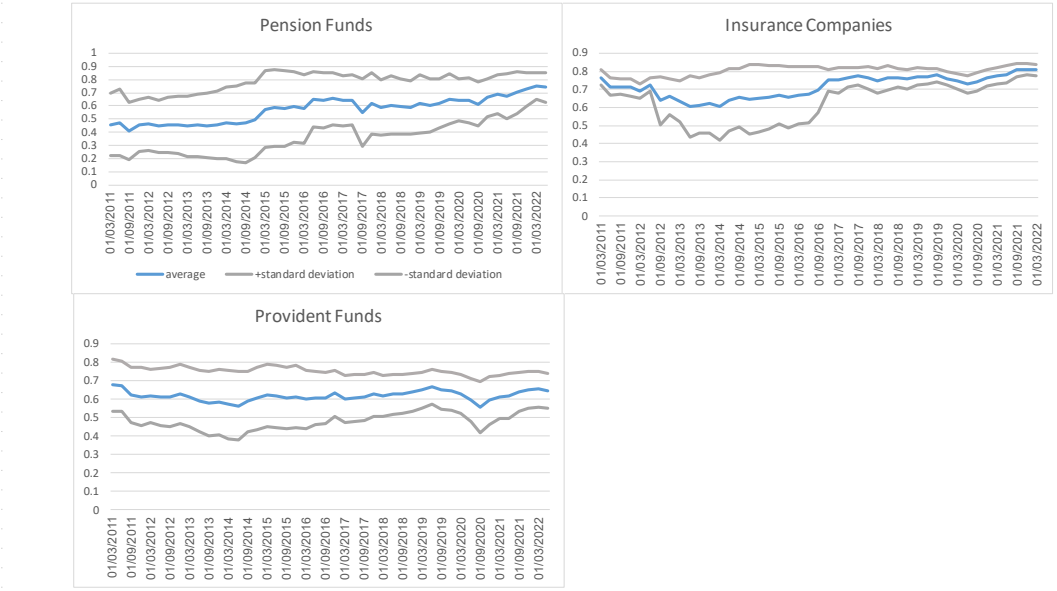


Diagram 7 shows the high level of similarity across all product types over time. However, we can see a slight increase in similarity for pension funds. For insurance companies and provident funds, the similarity appears to be stable over time, with no significant change.

5. System description by means of network graph

We can create a cosine similarity diagram, indicated by G, based on the matrix shown above as a heat map. This diagram has vertices representing the management companies and edges with weights connecting each company pair, representing the cosine similarity between each company pair. Such a diagram is very dense, as it contains an edge for each company pair. Therefore, we aim to filter out this diagram while maintaining the major connectivity patterns in the system. To this end, we use a filtering method resulting in a maximal planar graph. A maximal planar graph is a method for filtering a dense graph, where the large number of edges makes it difficult to see a clear picture of the system represented by the graph. The key idea of this filtering method involves filtering the graph so as to obtain a maximal graph in terms of the sum of cosine similarities, subject to constraints on the graph layout. This method typically preserves the 3-4 primary cliques (Massara et al. 2017). In a maximal planar graph, the graph is constrained to be planar, i.e. with no intersecting edges. Diagram 8 below shows a maximal planar graph for management companies, as of the second quarter of 2022.

Diagram 8 – Maximal planar graph of management companies' asset portfolios, Q2/2022

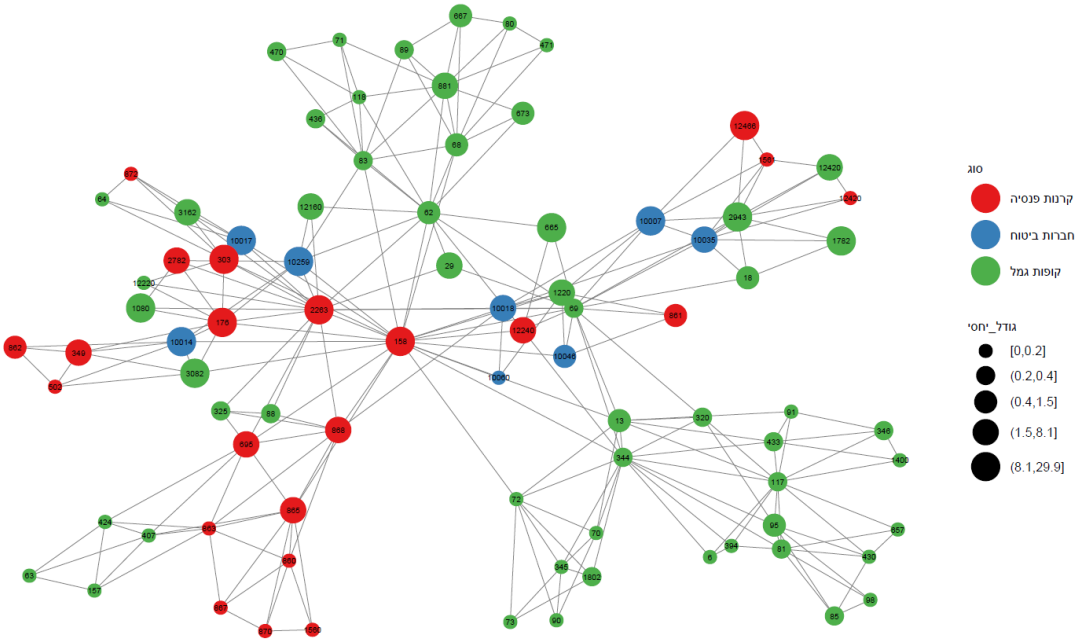


Diagram 8 shows that similarity is typically high between management companies for the same product type – evident in multiple clusters in the graph which mostly consist of vertices of the same color, i.e. the same type of institutional investor. Thus, for example, we see two clusters (top center and bottom right) of provident funds (in green) and a cluster (bottom left) where most pension funds are concentrated. Insurance companies appear to be less concentrated in the center than on the edges. The diagram shows, however, that similarity also exists between management companies across different product types.

6. Conclusion

This document presents commonly used methods for examining the extent of concentration and similarity across institutional investors. These methods and benchmarks are used to analyze the structure of the financial system, and to identify vulnerabilities due to overlapping portfolios of the management companies. This document shows that in Israel there is high concentration across all product types, reflected by the low effective number of management companies compared to their absolute number, as well as by strong similarity among these management companies' asset portfolios, primarily for insurance companies and pension funds, as reflected in the heat maps. The network graph allows us to identify clusters of similarity between management companies of the same type, as well as overlap between companies across different product types.

References

Barucca, P., T. Mahmood, and L. Silvestri (2021). “Common Asset Holdings and Systemic Vulnerability Across Multiple Types of Financial Institution”. *Journal of Financial Stability*, 52: 100810.

Elsinger, H., A. Lehar, and M. Summer (2006). “Risk Assessment for Banking Systems”. *Management Science*, 52(9): 1301–1314.

Girardi, G., K.W. Hanley, S. Nikolova, L. Pelizzon, and M.G. Sherman (2021). “Portfolio Similarity and Asset Liquidation in the Insurance Industry”. *Journal of Financial Economics*, 142(1): 69–96.

Kosenko, K. and N. Michelson (2022). “It Takes More than Two to Tango: Multiple Bank ”Lending, Asset Commonality and Risk”. *Journal of Financial Stability*, 61: 101040.

Levy-Carciente, S., D.Y. Kenett, A. Avakian, H.E. Stanley, and S. Havlin (2015). “Dynamical Macroprudential Stress Testing Using Network Theory". Journal of Banking & Finance, 59: 164–181.

Massara, G.P., T. Di Matteo, and T. Aste (2017). “Network Filtering for Big Data: Triangulated Maximally Filtered Graph”. *Journal of Complex Networks*, 5(2): 161–178.

Poledna, S., S. Martínez-Jaramillo, F., Caccioli, and S. Thurner (2021). “Quantification of Systemic Risk from Overlapping Portfolios in the Financial System”. *Journal of Financial Stability*, 52: 100808.