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Elimination of characteristics concerning the performance of open-ended equity funds using PCA

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Abstract

From an investor's point of view, the appropriate selection of a fund is an important issue. When making such a choice, many elements should be considered. These include not only the fund's rate of return or its risk, but also the comparison of the fund's results with an appropriate benchmark. The aim of the research was to apply principal component analysis (PCA) to reduce the dimension of the indicators that help the investor in selecting a fund. The subject of the study was 15 equity funds that had been on the Polish market for many years. The research showed that it is possible to reduce the primary variables to two dimensions.

Key words: PCA, investment funds, decision-making, tau-Kendall correlation coefficient, investment efficiency.

1. Introduction

The making of an investment decision in the case of mutual funds takes place both at the level of the managers, who have to decide on a specific investment goal, and of the investor. From the point of view of an investor intending to entrust his or her financial funds to investment funds, an important issue is the appropriate choice of fund (Soongswang and Sanohdontree, 2011). Making such a decision is not always obvious, as there are many elements that should be considered when making such a choice. These are, for example, the fund's rate of return, its risk, but also the comparison of the fund's results with the appropriate benchmark. In practice, it is very difficult for an investor to assess a fund in terms of many factors (Kozup et al. 2008), which raises the question of which variables are the most important to guide such a choice. So, there is a need for dimensionality reduction of the variables. This is enabled by principal component analysis (PCA).

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The aim of the research is therefore to try to look for the main factors determining the choice of an appropriate investment fund in terms of its performance and risk. The research concerns the period from March 12, 2020 to February 23, 2022 and includes fifteen equity funds that have been operating on the Polish market for several years. The period adopted for the research was characterized by an upward trend in the value of participation units. The reaction to the pandemic took place just before the pandemic period (Żebrowska-Suchodolska and Piekunko-Mantiuk, 2022). Therefore, this period was adopted to search for the variables determining fund selection. The subject of the study was 15 equity funds that have been in the market for many years. Principal component analysis (PCA) was used as the research method. The research carried out fits into the issues of investment decision-making and investment efficiency. They also give concrete indications about the choice of appropriate measures for investors. Due to the interconnection of markets with each other, research results may be the basis for making decisions in other markets.

The work is organized as follows. The Chapter 2 contains a literature review. The Chapter 3 presents the characteristics of equity funds against the background of all investment funds in Poland and Chapter 4 presents the methods used for the research, the results of which are presented in Chapter 5. The work ends with the conclusions in Chapter 6.

2. Review of the literature

Investment funds are often assessed in terms of their rate of return and associated risk (Sorros 2003). Risk can be understood here in many ways, whether in a negative, neutral or value at risk context (Rutkowska-Ziarko et al., 2022) (Żebrowska-Suchodolska, 2021, 2022). In order to compare the performance of funds, their performance indicators are determined. With their help, it is possible to compare funds within a group, between groups (Bliss and Potter, 2002) against an established benchmark (Basu and Huang-Jones, 2015), or between different markets and countries (Huij and Post, 2011). Most studies on fund performance are for the US market (Shukla and Singh, 1997). Studies for European market funds are often performed for single countries ((Leite and Cortez, 2013), (Babalos et al., 2012), (Fereira, et al., 2013), (Białkowski and Otten, 2011), (Vidal-García, 2013)) or a group of countries (Otten and Bams, 2002; Božović, 2021). Most studies indicate that funds underperform the market. European funds that have been on the market for a long time are characterized by poor results (Graham et. all, 2020), but also funds investing actively do not give better results than those that invest passively (Berk and van Binsbergen, 2012). Although there are results that exceed the market (Kosowski et al., 2006), they often lack stability (Mateus et al., 2019).

Studies of fund performance can be carried out using different types of measures. These can be both classical and non-classical indicators, which are based on the semi-standard deviation, the value at risk (Małecka, 2021) or the maximum drawdown (Żebrowska-Suchodolska, 2023). It is also important to look for factors that significantly influence fund performance (Filip and Rogala, 2021).

Due to the multitude of indicators, it is difficult for an investor to choose the right one. Research shows that many of them are correlated with each other (Żebrowska-Suchodolska, 2017), but there is still a large number of indicators to choose from. One of the methods that can be used here can be principal component analysis (PCA) (Abdi and Williams, 2010). It is used to reduce the dimension of the space under consideration, which makes it possible to obtain a description of the new variables in the new space to determine the structure of the data set under study (Jackson, 2005). The PCA method thus avoids the curse of dimensionality when dealing with linear data. Reducing redundant variables allows the elimination of those that are not very relevant. Computationally, this reduces memory consumption. The PCA method is used for many economic and social issues (Vyas and Kumaranayake, 2006). In finance, for example, it is used to reduce macroeconomic factors affecting returns (Bilson et al., 2001) and the classification of companies in terms of financial ratios (Yap et al., 2013).

The PCA method for investment funds was used by Zamojska (2013), but her research covered the period 2008-2012. These are the only studies that the author found regarding the reduction of the dimension of performance indicators. Therefore, there is a need to continue this research.

This paper fills a gap in the use of the PCA method to indicate indicators in a two-dimensional space for investment funds. In addition, the author's intention is to obtain pairs of indicators to evaluate the funds. The obtained pairs of indicators will help the investor to decide on an appropriate fund choice guided only by a minimum number of indicators.

3. Equity funds in Poland

Investment funds have been operating on the capital market in Poland for almost thirty years. They account for almost 10% of the household savings portfolio. The basic classification of funds under the Act on Investment Funds and Management of Alternative Investment Funds is the division into: open-ended funds, specialised open-ended funds and closed-ended funds. Table 1 shows the number of these funds for the last five years, i.e. the period 2017–2021.

Table 1: Number of investment funds (data as at Q4 of the year).

Funds and sub-funds	2017	2018	2019	2020	2021
Open-ended funds	334	326	327	312	304
Specialized open-ended funds	294	301	450	311	320
Closed funds	748	679	614	537	503

Source: Own compilation based on NBP.

At the end of 2021, there were 60 investment fund companies operating in Poland. They managed 1127 funds and sub-funds. At that time, there were 304 open-ended funds, which accounted for 26.97%. Over the five-year period, the percentage share of these funds in the number of total funds changed only slightly. The smallest share of open-ended funds was recorded in 2019 and they then accounted for 23.51%. The increasing number of specialised funds resulted in open-ended funds taking third place in terms of their number in 2019 and 2021.

In terms of net asset value (Table 2), closed-end funds accounted for the largest percentage of total assets. Open-ended funds came second. Considering different types of funds, equity funds ranked second in terms of net assets, after debt funds. This position did not change over the period under consideration. The net asset value of equity funds amounted to PLN 25.82 billion at the end of 2021.

Table 2: Net asset value of investment funds (in billion PLN), data as at Q4 of the year

Funds and sub-funds	2017	2018	2019	2020	2021
Open-ended funds	334	326	327	312	304
Specialized open-ended funds	294	301	450	311	320
Closed funds	748	679	614	537	503
Equity	20.04	16.85	16.85	18.41	29.53
Balanced	7.25	6.21	4.91	5.21	5.80
Debt securities	52.83	64.82	76.70	78.05	68.8
Stable growth	10.64	9.20	7.65	7.59	9.01
Other	4.93	4.98	3.43	3.7	1.24

4. Research methodology

The starting point is the daily rate of return, the risk and the performance indicators based on them. The rate of return is understood as $\frac{r_t - r_{t-1}}{r_{t-1}}$, where r_t,r_{t-1} are the values of the fund's participation units at time t and t-1.

The second important measure identifying an asset is risk. This is most commonly understood as negative and positive deviations from the mean, i.e. standard deviation. From an investor's point of view, however, what is more important is the loss that can be incurred from a given investment, or the probability of this loss. Therefore, in addition to standard deviation (S), semi standard deviation (S-), value at risk (VaR), conditional value at risk (CVaR), Ulcer index(U) and maximum drawdown (MDD) were also adopted for the study. These are described by the following formulas:

$$S = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}\left(r_t - \bar{r}\right)^2}, \tag{1}$$

where $\bar{r}$ is the average return and n is the sample size

$$S^- = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n} d_t\left(r_t - r_{\min}\right)^2}, \tag{2}$$

where $r_{\min}$ is the minimum required rate of return (here $r_{\min}$ =0) , and d_t is the zero if $r_t > r_{\min}$ and 1 otherwise.

$$VaR = -\left(\bar{r} + q_\alpha S\right), \tag{3}$$

where q_α is the quantile of the standardised normal distribution.

$$CVaR = \bar{r} + \frac{\varphi_{1-\alpha}}{\alpha} S, \tag{4}$$

where $\varphi_{1-\alpha}$ is density function of the standardised normal distribution.

$$U = \sqrt{\frac{1}{n}\sum_{t=1}^{n} D_t^2}, \tag{5}$$

where D_t is the relative decrease in the value of fund A shares in period *t*.

$$MDD = \min D_t \tag{6}$$

The combination of return and risk is represented by investment performance indicators, for which references include acceptable investment return, benchmark, or risk-free assets. These are taken into account by the following indicators: Sharpe, Sortino, Calmar, Martin, RVaR and CS. The selected performance indicators are described by the following formulas:

$$Sharp = \frac{\bar{r} - r_f}{S}, \tag{7}$$

where r_f is the average risk free rate.

$$Sortino = \frac{\bar{r} - r_{\min}}{S^-} , \tag{8}$$

$$C = \frac{\bar{r}}{MDD} , \tag{9}$$

$$M = \frac{\bar{r} - r_f}{U} , \tag{10}$$

$$RVaR = \frac{\bar{r} - r_f}{VaR} , \tag{11}$$

$$CS = \frac{\bar{r} - r_f}{CVaR} . \tag{12}$$

The large number of indicators and measures creates the need to reduce them so that the investor can make a decision on the basis of the fewest number of variables that do not duplicate information. The tau-Kendall correlation coefficient determined here makes it possible to examine the relationship between the measures adopted and the uncorrelated variables are the starting point for further considerations. Although the dimension of the uncorrelated variables is smaller than that of all variables, it is often still too large to make an investment decision. For this purpose, principal component analysis (PCA) was used. It allows to reduce the dimension of the underlying variables, leaving the most relevant ones, which makes the resulting group more homogeneous.

Principal component analysis (PCA) was first described by Pearson (1901) and developed by Hotteling (1933, 1936).

The starting point of the PCA method is the determination of the principal components, which are a linear combination of the primary variables:

$$Z_i = a_{i1}X_1 + a_{i2}X_2 + \ldots + a_{ip}X_p ,$$

where $X_1, X_2, \ldots, X_p$ are the primary variables.

The principal components are the result of determining the eigenvalues and eigenvectors from the following equation:

$$(M - \lambda I)a = 0 ,$$

where λ are the eigenvalues of the matrix M, M - the covariance matrix of the primary variables, I - the unit matrix, and $a = (a_{i1}, a_{i2}, , , , , a_{ip})$ the eigenvector corresponding to the i-th eigenvalue. A non-zero solution exists when $\lfloor M - \lambda I \rfloor = 0$. The largest eigenvalues of the covariance matrix M are searched in order. The coefficients of the corresponding eigenvector are the coefficients $a_{i1}, a_{i2}, \dots, a_{ip}$ of the principal components which correspond to the i-th largest eigenvalue of the covariance matrix M.

The resulting principal components are uncorrelated with each other, and their final separation can be based on the Kaiser criterion (1960), or the percentage of explained variability by the principal components. Often, as few as two components may be sufficient here, especially if they exceed 75% of the total variability of all variables (Morison 1990).

The application of the described steps will contribute to the verification of the following research theses and hypotheses:

T1: a reduction in the indicators describing the funds in terms of their performance will help the investor in making his investment decision.

H1: the fund selection decision can be made on the basis of two indicators.

4. Results of the study

The subject of the research were fifteen equity funds that have been operating on the market for several years. They were: Allianz Polskich Akcji, Esaliens Akcji, Generali Korona Akcje, Investor Akcji Spółek Dywidendowych, Investor Akcji, Investor Top 25 Małych Spółek, Millennium Akcji, NN Akcji, Novo Akcji, Pekao Akcji Polskich, Pzu Akcji Krakowiak, Rockbridge Akcji Małych i Srednich Spółek, Rockbridge Akcji, Santander Akcji, Skarbiec Akcja. The research was based on the daily values of participation units of these funds in the period from March 12, 2020 to February 23, 2022. In the case of equity funds, the research period was characterised by an upward trend, as the reaction to the pandemic took place immediately earlier (Żebrowska-Suchodolska, Piekunko-Mantiuk 2022). Therefore, this period was selected to search for variables determining the choice of a fund and to reduce their dimensions.

For the funds, the average rate of return was calculated as well as the measures described by formulas (1) - (12) for which the tau-Kendall correlation coefficient was determined. The values of the tau-Kendall correlation coefficient are presented in Table 3.

The values of the tau-Kendall correlation coefficient indicated the existence of a relationship between many analyzed indicators. Thus, they provided a basis for removing them from further considerations. After this selection, the following groups of indicators not correlated with each other were selected:

1) $\bar{r}$, S, VaR, CVaR, MDD
2) $\bar{r}$, S, MDD, C, RVaR, CS
3) S^-
4) $\bar{r}$, VaR, MDD, RVaR, CS

5) $\bar{r}$, CVaR, MDD, RVaR, CS
6) U
7) $\bar{r}$, S, VaR, CVar, MDD, Sharp, Sortino, C, M, RVaR, CS
8) MDD, Sharpe
9) MDD, Sortino
10) S, MDD, C
11) MDD, M
12) S, VaR, CVaR, MDD, RVaR
13) S, VaR, CVaR, MDD, CS

Table 3: The values of the tau-Kendall correlation coefficient.

Specification	$\bar{r}$	S	S^-	VaR	CVaR	U	MDD	Sharp	Sortino	C	M	RVaR	CS
$\bar{r}$	1	-0.26	**-0.45**	-0.35	-0.34	**-0.50**	0.15	**0.79**	**0.79**	**0.58**	**0.79**	**1**	**1**
S		1	1	**0.81**	**0.93**	**0.49**	-0.31	**-0.47**	**-0.47**	-0.30	**-0.39**	-0.26	-0.26
S^-			1	**0.91**	**0.89**	**0.60**	**-0.39**	**-0.66**	**-0.66**	**-0.45**	**-0.54**	**-0.45**	**-0.45**
VaR				1	**0.99**	**0.59**	-0.37	**-0.57**	**-0.57**	**-0.39**	**-0.49**	-0.35	-0.35
CVaR					1	**0.58**	-0.36	**-0.56**	**-0.56**	**-0.38**	**-0.48**	-0.34	-0.34
U						1	**-0.45**	**-0.68**	**-0.68**	**-0.73**	**-0.71**	**-0.50**	**-0.50**
MDD							1	0.28	0.28	0.18	0.31	0.14	0.14
Sharp								1	**0.96**	**0.71**	**0.85**	**0.79**	**0.79**
Sortino									1	**0.68**	**0.81**	**0.79**	**0.79**
C										1	**0.79**	**0.58**	**0.58**
M											1	**0.79**	**0.79**
RVaR												1	1
CS													1

*values in bold are statistically significant at the 0.05 significance level

Source: Own calculation using Statistica.

For each group containing more than two variables, the PCA method was used to reduce the dimension and find the variables with the highest percentage of principal components explaining the variability. The first two components explained more than eighty percent of the overall variability, so on the basis of the scree plot criterion they can be considered sufficient to decide on the number of principal components.

A representation of the performance indicators in terms of the first two principal components is shown in Figure 1.

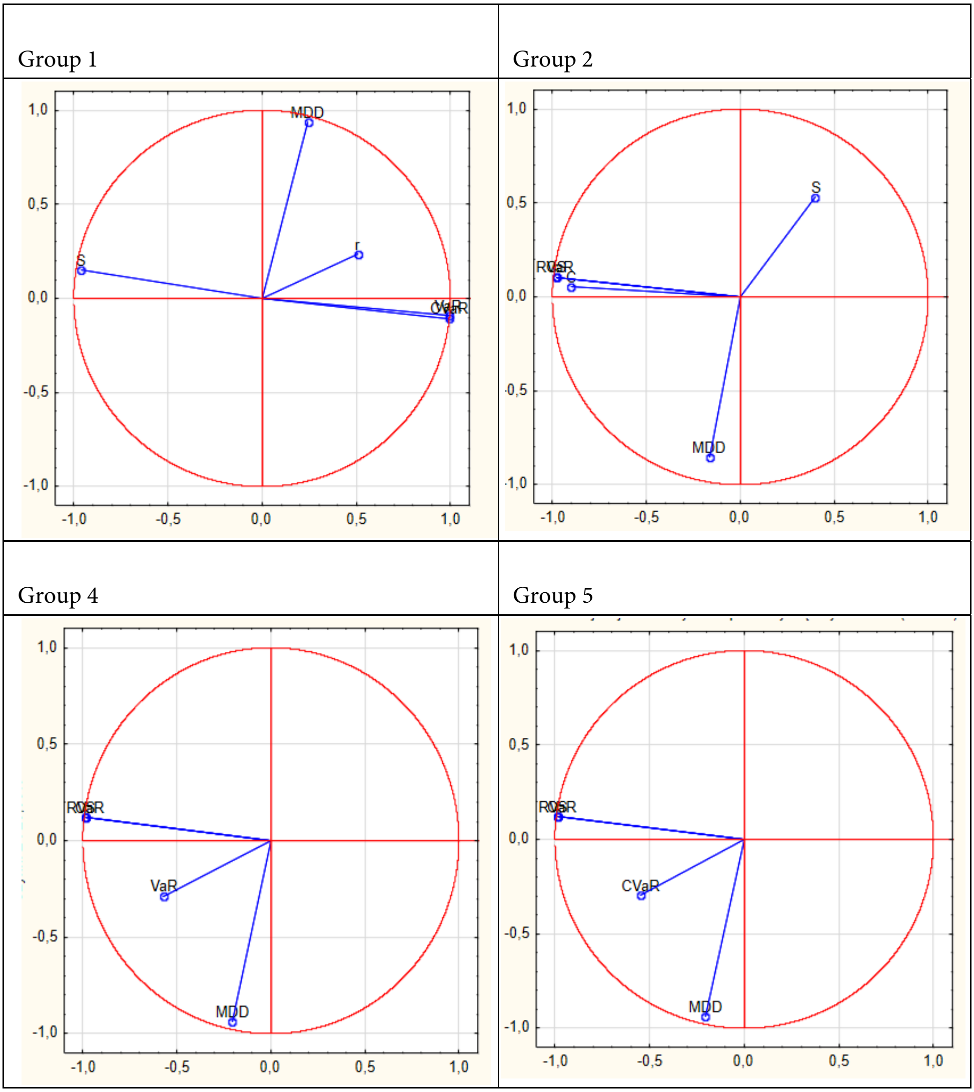

Figure 1: A representation of the performance indicators in terms of the first two principal components

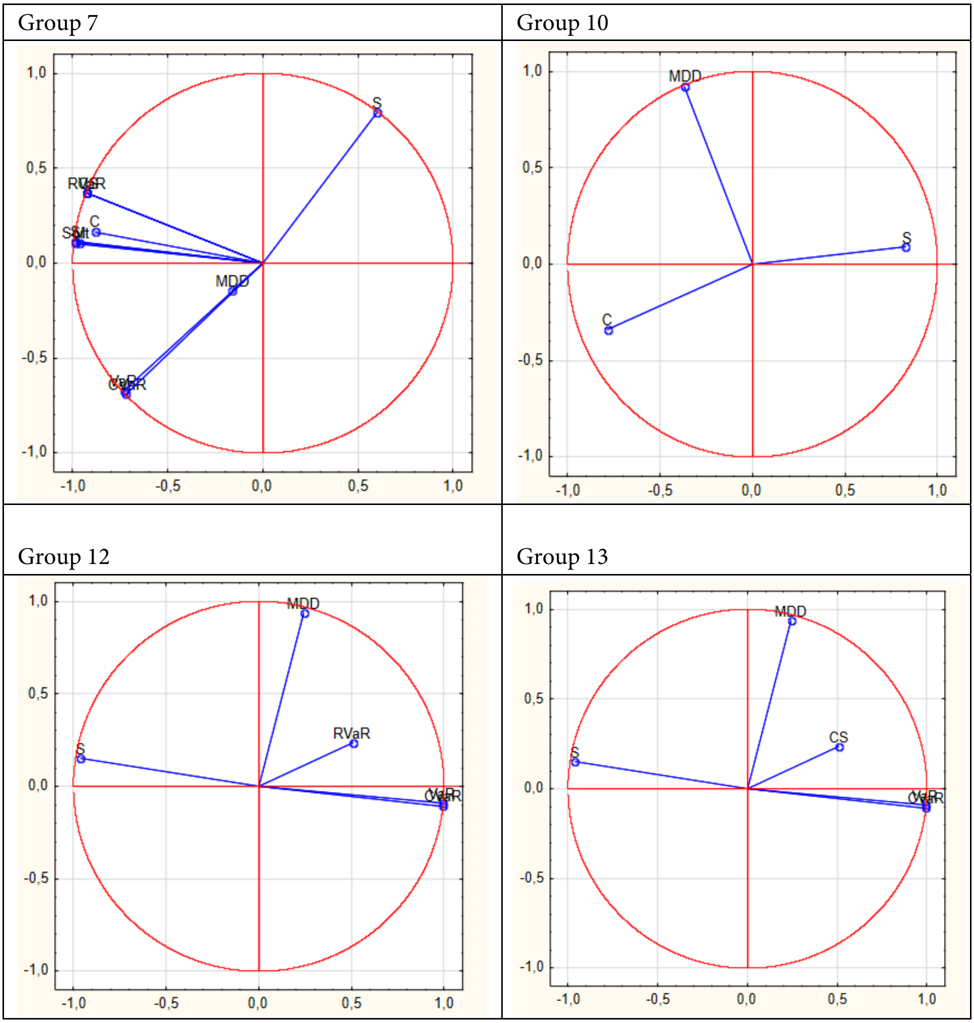

Figure 1: A representation of the performance indicators in terms of the first two principal components (cont.)

Source: Own calculation using Statistica.

In Figure 1, for each group are placed points (charges) in the unit circle. The position of the point corresponds to the information of this variable carried by the first two principal components. The closer the point is to the edge of the circle, the better it is represented by the principal components. The position of the points relative to each other, in turn, provides other information. The close position of the vectors indicates the existence of a positive correlation between the variables. Their position on the opposite side indicates negative correlation. Their perpendicular position relative to each other indicates that the variables are uncorrelated.

Projecting the indicators onto the plane of the first two components shows that in most cases the points representing the individual indicators lie at or close to the edge of the circle. This indicates that these indicators are well represented by the principal components and that they carry most of the information contained in the output indicators. In addition, the measures are located in other parts of the circle indicating that they carry quite different information. Thus, their designation here is important for the overall assessment of the fund.

The largest percentages of indicators in each principal component allow the most important indicators to be identified in terms of the importance of the information they convey. These are the following indicators in each group:

1) MDD, VaR/CVaR

2) MDD, r/RVar/CS

4) r/RVar/CS, MDD

5) r/RVaR/CS, MDD

7) Sharp/Sortino/M, S

10) S, MDD

12) VaR, MDD

13) VaR, MDD

Principal component analysis also allows investment funds to be shown in a two-dimensional factor space. The projection of the funds on the factor plane is shown in Figure 2.

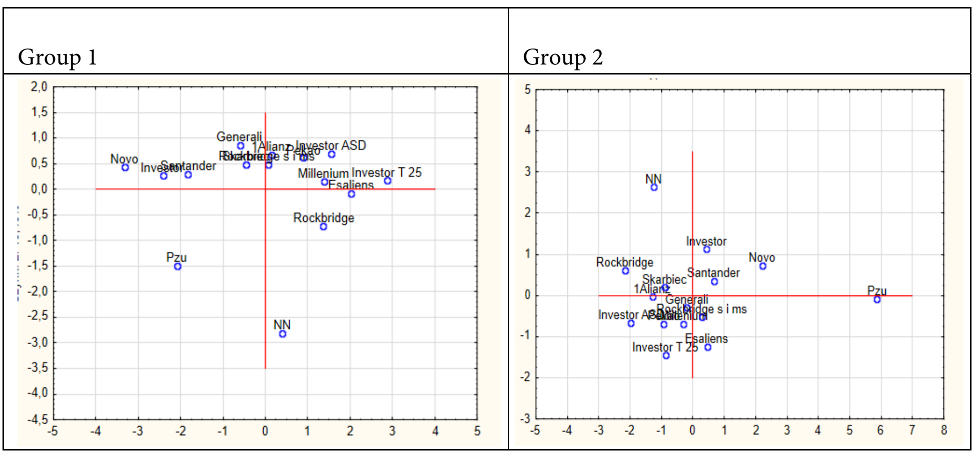

Figure 2: The projection of the funds on the factor plane

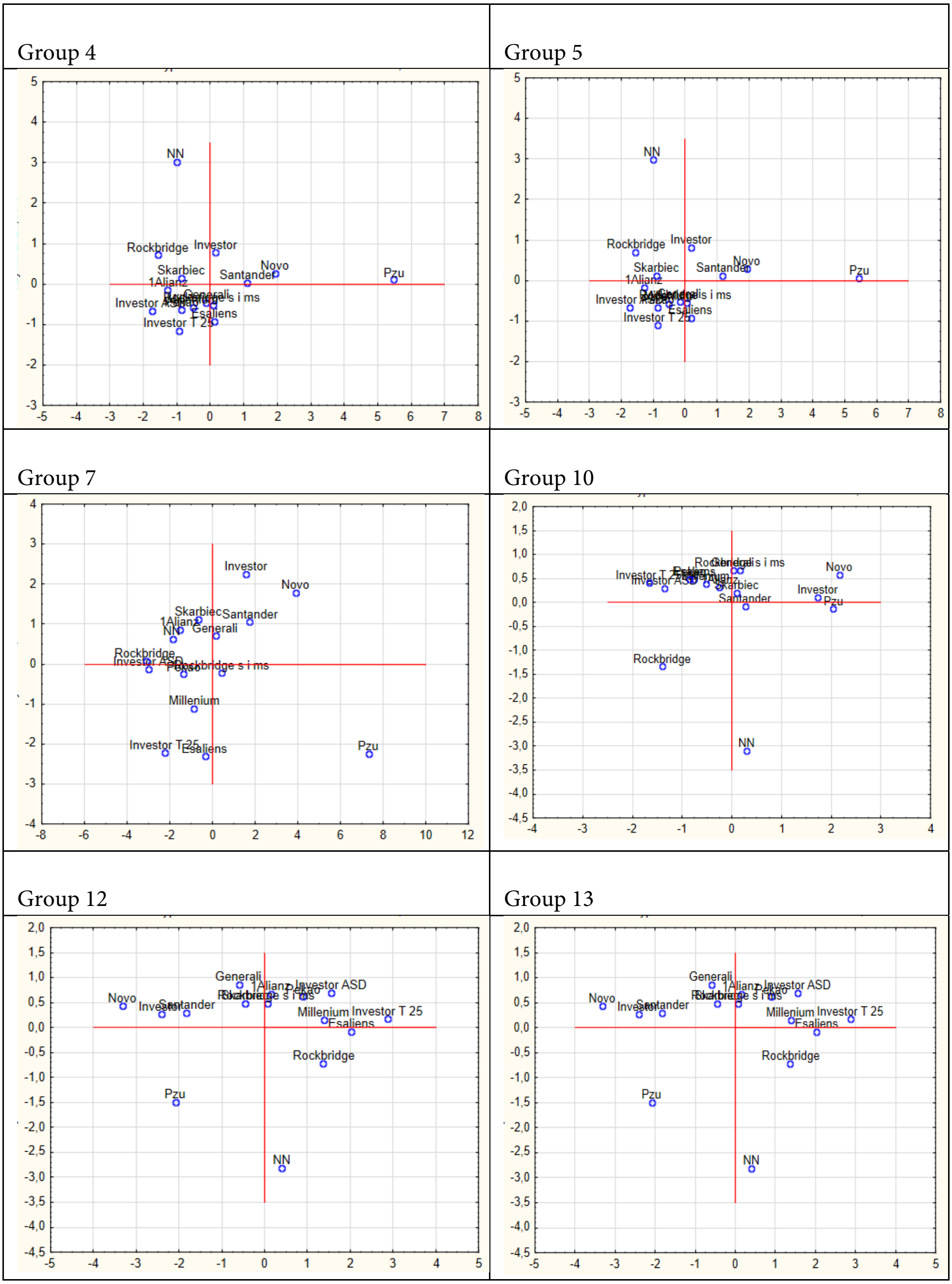

Figure 2: The projection of the funds on the factor plane (cont.)

Source: Own calculation using Statistica.

The marked points correspond to the funds. They are plotted on the plane of the first two principal components. From the graph, you can read the values of the first two components for each fund. In addition, the position of the points shows the similarity between the funds. The closer the funds are located, the more similar they are to each other.

The projection of the funds onto the plane of the first two components indicates the existence of three clusters of points in most cases. Only two clusters are discernible in the case of group 7. The first cluster contains the majority of funds, while the others contain only individual funds. Similar results in terms of the measures considered are indicative of a similar investment policy pursued by managers. This is because the funds in most cases only emulate the market, and the skills of selectivity and market timing are present in single cases (Żebrowska-Suchodolska and Karpio, 2018). Outliers of values from the largest cluster occurred for PZU, NN and Rockbridge funds in group 10. They constituted single clusters. Therefore, in the case of these funds, the results of the measures taken into account differ significantly from the others.

5. Conclusions

The aim of the research was to try to look for the main factors determining the choice of an appropriate investment fund in terms of its performance and risk. Principal component analysis was used for this. The study covered the period from March 12, 2020 to February 23, 2022 and involved fifteen equity funds that had been operating on the Polish market for several years. 13 groups were selected for the study. The groups were selected in terms of correlation of indicators. They contained from 1 to 10 indicators.

The research showed that it is possible to reduce the primary variables to two dimensions, confirming the hypothesis H1. Two indicators were also indicated by Zamojska as sufficient to assess the performance of the funds. This will help the investor to make the right decision on the fund selection (T1) by taking only two indicators. To evaluate a given investment in funds, the investor should choose the MDD measure and some measure of risk (VaR/CvaR/S).

Besides, the pairs of indicators included in the principal components have been placed in other parts of the circle, allowing the investor to assess the fund from the point of view of completely different information. The resulting indicators found in each group are based on a combination of classical and non-classical measures. It is only with this combination that the contribution of the output variable to the principal component is best. Some of the pairs contain only the risk measures themselves, which shows how important they are when evaluating a fund and from the point of view of the loss that an investor may suffer.

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