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THE CLASSIFICATION OF POLISH MUTUAL BALANCED FUNDS BASED ON THE MANAGEMENT STYLE − QUANTILE REGRESSION APPROACH

Abstract: Style Analysis allows to assess impact of factors representing investments in asset classes on funds' rate of returns. When distribution of return rates is asymmetric, the application of classical Sharpe Style Analysis may lead to incorrect inference about model coefficients. Quantile Style Analysis investigates dependencies between fund returns and the risk factors for the quantile of the distribution. The paper's aim is to investigate the impact of the investments in the stocks and bonds on the balanced mutual funds returns by Quantile Style Analysis and to assess the usefulness of the quantile approach to the style analysis of the funds. We compare both the style shares for different quantiles for given fund and the funds classifications according to the style shares obtained for quantile and classic approach.

Key words: Quantile Style Analysis, quantile regression, mutual balanced funds.

1. Introduction

The funds' managers invest in assets with different risk characteristics to maximize the portfolio's expected rate of return. Performance attribution is an important part of a fund's portfolio management assessment. It compares the portfolio's total rate of return to the return from a benchmark portfolio and calculating an added value defined as the excess return over the rate of return from the benchmark (market) portfolio.

One of the statistical tools for the performance attribution of investment portfolios consisting of different asset classes is a style analysis introduced by William Sharpe in 1992. The term *style* means an investment strategy that allows a fund to reach predefined results. The factor style analysis aims at attributing the fund's rate of return to rates of return from indices representing the fund's investments in different asset classes. Therefore it allows to establish the influence of the fund's investments in different asset classes on the fund's total rate of return in a given period of time.

Standard linear model of the style analysis is multiple regression model of the fund's conditional expected rate of return on rates of return from indices representing different asset classes. Its parameters (*style shares*) are estimated by the least squares method (LSM) subject to non-negativity and summing to one conditions. However the classical regression offers only a partial view on the dependence between variables since it focuses on the central part of dependent variable distribution. This can potentially have serious consequences for the correct inference on the impact of factors on changes of dependent variable, especially when the error term is non-normal and heteroscedastic or when distribution is asymmetric or fat-tailed as well as in the case of outliers or more general uncertainty over the shape or type of error term distribution.

We generalize classic Sharpe style analysis models on quantile constrained multiple regression models that are robust to classical Sharpe style analysis assumption. The aim of the paper is to assess the impact of some factors (style shares) on the whole conditional distribution of balanced mutual funds returns and to examine whether the quantile approach is useful for style analysis of balanced mutual funds. The usefulness of the quantile approach is examined from two perspectives. First, we check if for a given fund structures of estimated style, shares are homogeneous for different quantiles. Second, we examine if the funds differ according to the style exposition for a given quantile and whether possible discrimination of the funds has the same character for different parts of distribution.

For this reason we classify the funds according to the style shares obtained for different quantiles and we compare the results with the classification obtained for style shares from least squares approach.

2. Classical Sharpe style analysis model

The relationship between a fund's rate of return and rates of return from indexes representing different asset classes in period t, $t = 1, 2, \ldots, T$, is given by:

$$R_t = \beta_1 F_{t1} + \beta_2 F_{t2} + \ldots + \beta_k F_{tk} + \varepsilon_t, \tag{1}$$

where: R_t – fund's rate of return in period t,
F_{ti}, $i = 1, 2, \ldots, k$ – a rate of return from the index i in period t,
β_i, $i = 1, 2, \ldots, k$ – the i-th parameter of the model describing sensitivity of R_t to F_{ti} (i-th style share),
ε_t – error term.

Let $\mathbf{R} = (R_1, R_2, \ldots, R_t)'$, $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_T)'$, $\mathbf{F} = (\mathbf{F}_1, \mathbf{F}_2, \ldots, \mathbf{F}_T)'$, where $\mathbf{F}_t = (F_{t1}, F_{t2}, \ldots, F_{tk})'$ means a random vector of rates of returns from the indexes in period t. A vector of unknown parameters $\boldsymbol{\beta} = (\beta_1, \beta_2, \ldots, \beta_k)'$ represents the set of style shares defining a portfolio of k asset classes. The Sharpe style analysis model main assumptions are as follows: $\mathbf{1}' \boldsymbol{\beta} = 1$, $\boldsymbol{\beta} \geq 0$, where $\mathbf{1}$ is k-dimensional vector of ones; the error terms ε_t are independent and identically distributed random variables such that $E(\varepsilon_t) = 0$, $D^2(\varepsilon_t) < \infty$, $t = 1, 2, \ldots, T$; the vectors $(R_t, \mathbf{F}_t')$ for every $t = 1, 2, \ldots, T$ are independent and identically distributed; the vector $\mathbf{F}_t$ and the error term ε_t are uncorrelated for every $t = 1, 2, \ldots, T$.

Normality assumption of the error term is necessary for classical inference on statistical significance of the model's parameters. In the case of non-normality least squares estimators are not efficient. Moreover, variance estimates are incorrect, which results in low power of classical significance tests.

Let r_t and $\mathbf{f}_t$ mean realizations of random variable R_t and random vector $\mathbf{F}_t$. Assume that matrix **F** has a rank k. In general the model (1) can be written as: $E(R_t|\mathbf{f}_t) = \mathbf{f}_t'\boldsymbol{\beta}$. A vector of least squares estimators of Sharpe style shares is a vector $\hat{\boldsymbol{\beta}}_{\text{SMNK}}$ that solves the following optimization problem:

$$\min_{\mathbf{b}\in\Re^k} \frac{1}{T}\sum_{t=1}^{T}(r_t - \mathbf{f}_t'\mathbf{b})^2 \tag{2}$$

under conditions: $\mathbf{1}'\,\mathbf{b} = 1$, $\mathbf{b} \geq \mathbf{0}$, where $\mathbf{1}$ is k-dimensional vector of ones.

The product of estimated parameters and the rates of return from the indexes represent an ideal market portfolio, also known as a passive portfolio. Rates of return from the passive part correspond to rates of return from a portfolio style, whereas rates of return from the active part correspond to the model's random errors. An investor's ability to select assets with returns higher than the market return in a given period is called a selection effect. Since this effect represents part of the return that exceeds return from a portfolio of randomly selected assets it could be attributed to active portfolio management strategy. On the other hand an allocation effect represents passive management strategy. In this context it could be said that passive managers can provide their customers only with an "investment style", whereas active ones provide both style and selection [Sharpe 1992].

Knowledge of estimators' of the model's parameters is essential for the interval estimation and testing hypothesis on the parameters' significance that are necessary for correct inference on the factors impact on the fund's rate of returns. The constraints imposed on the vector of the style coefficients, especially the non-negativity constraint, causes the fact that the exact distribution of the least squares estimates is unknown. Therefore non-standard estimation methods that account for the model risk as well as the estimation risk should be applied. The most widely used methods of this kind are Bayesian style analysis and Andrews asymptotic confidence intervals [Kim, White, Stone 2005]. Both approaches, based on the least squares estimation of conditional expected value of a dependent variable, give a statistically-correct confidence intervals as well as parameters significance tests, but the Andrews method is more sensitive for parameters that have a true value of 0 (these methods were employed for the style analysis of Polish mutual and pension funds in [Orwat 2008, 2009, 2011]). Employing quantile multiple regression for the style analysis aims at extracting additional information from the whole distribution of rates of return conditional quantiles.

3. Quantile regression

We analyse a problem of estimation of a vector of parameters $\boldsymbol{\beta}$ for a sample of independent observations r_t, $t = 1, 2, ..., T$ of a sequence of random variables R_1, R_2, ..., R_T taken with distribution $P(R_t < r) = \Im(r - \mathbf{f}_t\,'\boldsymbol{\beta})$, where $\mathbf{f}_t = (f_{t1}, f_{t2}, ..., f_{tk})'$ is a column $(T \times k)$ matrix of observations $\mathbf{F}$ and the distribution $\Im$ is unknown. Then a sample τ-th quantile $0 < \tau < 1$ is a solution of the following optimization problem:

$$\min_{b \in \Re} \left[\sum_{t \in \{t : r_t \geq b\}} \tau |r_t - b| + \sum_{t \in \{t : r_t < b\}} (1 - \tau) |r_t - b| \right]. \tag{3}$$

3.1. Quantile regression model

Linear quantile multiple regression[1] of order τ $0 < \tau < 1$ can be stated as:

$$R_t = \beta_1^{(\tau)} F_{t1} + \beta_2^{(\tau)} F_{t2} + \ldots + \beta_{tk}^{(\tau)} F_{tk} + \varepsilon_t^{(\tau)}, \; t = 1, 2, ..., T, \tag{4}$$

where: $\beta_i^{(\tau)}$, $i = 1, 2, ..., k$ – i-th model's parameter,

$\varepsilon_t^{(\tau)}$ – error term.

The only assumption that lies under the model (4) is a conditional distribution of τ-th quantile: $Q_\tau(R_t | \mathbf{f}_t) = \mathbf{f}_t\,'\boldsymbol{\beta}^{(\tau)}$, where $\boldsymbol{\beta}^{(\tau)} = (\beta_1^{(\tau)}, \beta_2^{(\tau)}, \ldots, \beta_k^{(\tau)})'$ and $Q_\tau(\varepsilon_t^{(\tau)} | \mathbf{f}_t) = 0$. A distribution of independent random variables $\varepsilon_t^{(\tau)}$ is left unspecified, which is the main virtue of the method as far as robustness to outliers is concerned. If $\boldsymbol{\beta}(\tau)$ is independent from τ, then the quantile model collapses to a model $E(R_t | \mathbf{f}_t) = \mathbf{f}_t\,'\boldsymbol{\beta}$ with a constant variance of a fit error. Otherwise the model implies the variance that a quantile of distribution of R_t depends on $\mathbf{f}_t$.

The model's estimation stage[2] is performed for a given quantile of order τ. Assuming that observations r_t, $t = 1, 2, \ldots, T$ are treated as a random sample of the regression process $u_t = r_t - \mathbf{f}_t\,'\boldsymbol{\beta}$ with unknown distribution $\Im$, Koenker and Basset [1978] defined a τ-th quantile regression estimator, which solves the following problem:

$$\min_{\mathbf{b} \in \Re^k} \left[\sum_{t \in \{t : r_t \geq \mathbf{f}_t\,'\mathbf{b}\}} \tau |r_t - \mathbf{f}_t\,'\mathbf{b}| + \sum_{t \in \{t : r_t < \mathbf{f}_t\,'\mathbf{b}\}} (1 - \tau) |r_t - \mathbf{f}_t\,'\mathbf{b}| \right]. \tag{5}$$

The problem (5) has always a solution; for continuous distributions it is unique. Since the problem (5) can be transformed to a linear optimization problem its solution can be found using an internal point method [Portnoy, Koenker 1997]. The approach is regarded as non-classic method due to its robustness. Like robust estimation, the

[1] The quantile regression models analysed in the paper do not have a constant.

[2] Semi-parametric character of estimation of the model (4) follows from the fact that the error term distribution is left unspecified. Parametric approach is also available provided the error term follows asymmetric Laplace distribution.

quantile approach detects relationships missed by traditional data analysis. Robust estimates detect the influence of the bulk of the data, whereas quantile estimates detect the influence of co-variates on alternate parts of the conditional distribution. Applications of the quantile regression method for Polish capital market can be found in [Trzpiot 2008, 2009a, b, c, 2010] among others.

4. Quantile style analysis model

Using the notation introduced earlier and generalizing classic Sharpe style analysis model to the quantile multiple regression the following quantile style analysis (QSA model) model can be obtained:[3]

$$R_t = \beta_1^{(\tau)} F_{t1} + \beta_2^{(\tau)} F_{t2} + \ldots + \beta_{tk}^{(\tau)} F_{tk} + \varepsilon_t^{(\tau)}, \quad t = 1, 2, ..., T, \tag{6}$$

where: R_t – fund's rate of return in period t,

F_{ti}, $i = 1, 2, \ldots, k$ – rate of return from the i-th style index in period t,

$\beta_i^{(\tau)}$ – i-th model's parameter representing sensitivity of the conditional τ-th quantile $0 < \tau < 1$ of dependent variable R_t to the i-th independent variable F_{ti},

ε_t – error terms.

Assumptions of the model are as follows: $\mathbf{1}'\boldsymbol{\beta}^{(\tau)} = 1$, $\boldsymbol{\beta}^{(\tau)} \geq \mathbf{0}$, $Q_\tau(R_t|\mathbf{f}_t) = \mathbf{f}_t'\boldsymbol{\beta}^{(\tau)}$, $Q_\tau(\varepsilon_t^{(\tau)}|\mathbf{f}_t) = 0$. Hence the quantile of rate of return from the fund's portfolio is linear function of a style exposition [Koenker, Ng 2005].

Parameter estimators of the model (6) are solutions to the problem (5) with respect to the following standard conditions: $\mathbf{1}'\,\mathbf{b} = 1$, $\mathbf{b} \geq \mathbf{0}$.

5. Hierarchical classification methods

In the set theory classification is defined as a non-empty family of subsets $\mathbf{K}_i$, $i = 1, 2, ..., k$ over a set of objects $\mathbf{K}$ that satisfies the conditions:

$$\mathbf{K}_i \cap \mathbf{K}_j = \phi, \quad \bigcup_{i=1}^{k} \mathbf{K}_i = \mathbf{K}, \; i \neq j, \quad i, j = 1, 2, ..., k, \tag{7}$$

where ϕ is an empty set. Hence classification is treated as a set of classes taken from the set of classified objects.

Hierarchical grouping procedures can be described with the following scheme: given a distance matrix for the set of objects it is initially assumed that every object forms a separate class. Then a pair of classes is found for which the distance between

[3] If $k = 1$, $\mathbf{f}_t = 1$ for all t, the problem (5) collapses to (3) and the smallest absolute error equals the median.

them is the shortest. They are merged and form one new class. Then the new distance matrix is calculated. The procedure continues until there is only one class left. Differences between methods come from different ways of calculating the distance between the classes. The most popular methods are: single linkage, complete single, unweighted pair-group average, weighted pair-group average, unweighted pair-group centroid, weighted pair-group centroid and Ward's method.

6. Results of empirical analysis

The management style of all of the 13 Polish Balanced Mutual Funds (PMBF) operating on the market during the whole period 02.01.2002–30.06.2008 was analysed. These were: Aviva Investors FIO subfundusz Aviva Investors Zrównoważony (AVI), BPH FIO Subfundusz BPH Aktywnego Zarządzania (BPH), Arka BZ WBK Zrównoważony FIO (BZW), DWS Polska FIO Zrównoważony (DWS), ING FIO Zrównoważony (ING), KBC Beta SFIO (KBC), Legg Mason Zrównoważony Środkowoeuropejski FIO (LEG), Millennium FIO Subfundusz Zrównoważony (MIL), Novo FIO Subfundusz Novo Zrównoważonego Wzrostu (NOV), Pioneer Zrównoważony FIO (PIO), PKO Zrównoważony FIO (PKO), Skarbiec FIO Zrównoważony (SKA), OFI Union Investment Zrównoważony (UNI).

In every model logarithms of monthly rates of return from a fund's participation unit prices are treated as dependent variables. The set of independent variables is the same for all models and consists of logarithms of monthly rates of return from the indexes representing a fund's investments in different classes of stocks and bonds. Among the independent variables there are the rates of return from sector stock sub-indices: WIG-banks ($WIG\text{-}_{ban}$), WIG-construction ($WIG\text{-}_{bud}$), WIG-informatics ($WIG\text{-}_{inf}$), WIG-food ($WIG\text{-}_{spo}$) and WIG-telecommunication ($WIG\text{-}_{tel}$); as well as

Table 1. Correlation matrix of independent variables in the Sharpe style analysis models

	$WIG\text{-}_{ban}$	$WIG\text{-}_{bud}$	$WIG\text{-}_{inf}$	$WIG\text{-}_{spo}$	$WIG\text{-}_{tel}$	PS	DS
$WIG\text{-}_{ban}$	1.00	**0.65**	**0.67**	**0.58**	**0.60**	0.19	**0.26**
$WIG\text{-}_{bud}$	**0.65**	1.00	**0.65**	**0.65**	**0.38**	0.01	0.08
$WIG\text{-}_{inf}$	**0.67**	**0.65**	1.00	**0.57**	**0.51**	0.08	0.14
$WIG\text{-}_{spo}$	**0.58**	**0.65**	**0.57**	1.00	**0.34**	0.10	0.08
$WIG\text{-}_{tel}$	**0.60**	**0.38**	**0.51**	**0.34**	1.00	–0.03	0.13
PS	0.19	0.01	0.08	0.10	–0.03	1.00	**0.50**
DS	**0.26**	0.08	0.14	0.08	0.13	**0.50**	1.00

Significant coefficients (significant level 0.05) are in bold.

Source: own calculations.

rates of return from the following bond accounting prices: 5-year fixed interest bonds (PS) and 10-year fixed interest bonds (DS).[4] The rates of return from sector indices WIG do not exhibit strong correlation with the rates of return from bonds. The correlation coefficients between the sector indices are different from 0 at the 0.05 significance level. This is also the case for correlation between sector indices and bonds PS and Ds (see Table 1).

Now, we discuss results for two example funds in detail to explain the idea of the research. For example for two funds, the Sharpe style analysis models obtained from the least squares estimation with parameters restrictions can be written as:

$$r_{UNI} = 0.17\,\mathrm{WIG}_{\text{-ban}} + 0.09\,\mathrm{WIG}_{\text{-bud}} + 0.07\,\mathrm{WIG}_{\text{-inf}} + 0.09\,\mathrm{WIG}_{\text{-spo}} + \\ + 0.08\,\mathrm{WIG}_{\text{-tel}} + 0.14\,\mathrm{PS} + 0.35\,\mathrm{DS}, \tag{8}$$

$$r_{DWS} = 0.16\,\mathrm{WIG}_{\text{-ban}} + 0.09\,\mathrm{WIG}_{\text{-bud}} + 0.06\,\mathrm{WIG}_{\text{-inf}} + 0.07\,\mathrm{WIG}_{\text{-spo}} + \\ + 0.07\,\mathrm{WIG}_{\text{-tel}} + 0.23\,\mathrm{PS} + 0.31\,\mathrm{DS}. \tag{9}$$

The results of the interval estimation and testing procedures based on the Andrews approach [Orwat 2011] are presented in Table 2. At the 0.05 significance level all parameters are different from 0. The set of independent variables given below is the result of carrying out the models' re-specification procedure that ruled out all variables that do not affect the endogenous variable in a statistically significant way.

Table 2. Results of the least squares with constrains estimation, interval estimation and testing procedures for parameters of models (8) and (9)

Index	Style share UNI	95% Andrews confidence intervals		*p*-value	Style share DWS	95% Andrews confidence intervals		*p*-value
		lower bound	upper bound			lower bound	upper bound	
$\mathrm{WIG\text{-}}_{\text{ban}}$	0.17	0.107	0.247	0	0.16	0.020	0.262	0
$\mathrm{WIG\text{-}}_{\text{bud}}$	0.09	0.013	0.163	0	0.09	0.002	0.163	0.01
$\mathrm{WIG\text{-}}_{\text{inf}}$	0.07	0.031	0.115	0	0.06	0.000	0.138	0.03
$\mathrm{WIG\text{-}}_{\text{spo}}$	0.09	0.008	0.166	0.01	0.07	0.013	0.140	0.02
$\mathrm{WIG\text{-}}_{\text{tel}}$	0.08	0.024	0.157	0	0.07	0.001	0.148	0.02
PS	0.14	0.088	0.148	0.05	0.23	0.059	0.405	0.05
DS	0.35	0.302	0.581	0	0.31	0.130	0.568	0
R^2	0.7885				0.7233			

Source: own calculations.

[4] The monthly accounting prices of bonds were calculated from daily prices, which were average prices for all bonds of a given type quoted in that day.

The value of the style shares estimated by the least squares approach suggest that the funds do not differ significantly according to the style (see Figures 1 and 2).

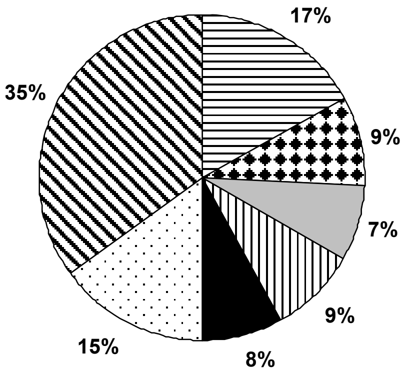

Figure 1. Style shares OLS for UNI fund

Source: own calculations.

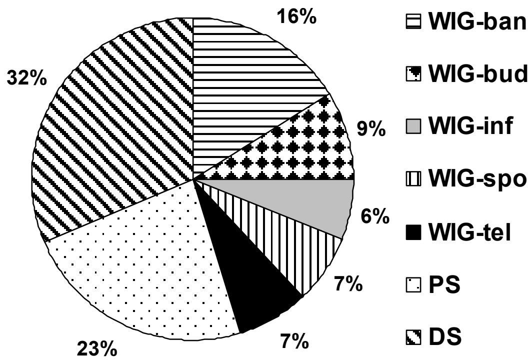

Figure 2. Style shares OLS for DWS fund

Source: own calculations.

However the comparative analysis of the style for different part of the distribution (for the quantiles of different order) suggests the opposite conclusions (Figures 3 and 4).

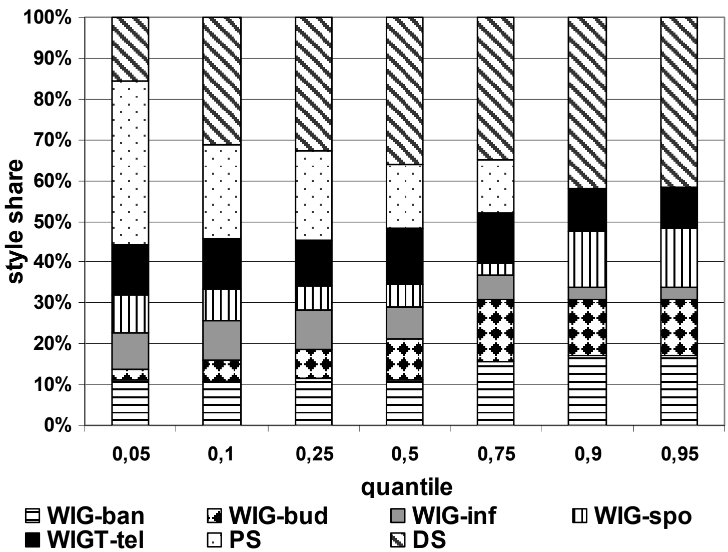

Figure 3. Style shares of UNI fund for different quantile orders

Source: own calculations.

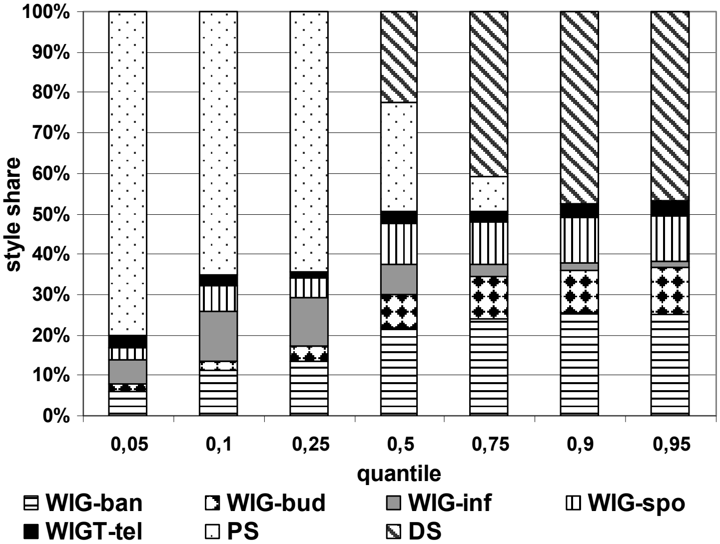

Figure 4. Style shares of DWS fund for different quantile orders

Source: own calculations.

As we expect the structure of shares obtained from least squares method is similar to shares obtained for quantile of order 0.5 (compare 4th bar of Figure 3 with Figure 1 and 4th bar Figure 4 with Figure 2). However the structure of shares for middle quantiles significantly differs from those estimated for extreme ones (for example for quantiles of order 0.05 and 0.95 – compare bars 1 and 7th on Figure 3). Estimated style shares for the quantiles of different order (0.05; 0.1; 0.25; 0.5; 0.75; 0.9; 0.95) depict significant heterogeneity of the funds' style expositions in the whole conditional distribution of returns. This is the case for both funds DWS and UNI.

Moreover, the two analyzed funds differ also for a given quantile order (compare bars of Figures 3 and 4, respectively). For example for the quantile of order 0.25 the structure of style shares of UNI fund considerably differs from the structure of style shares of the DWS fund. Namely for UNI fund, low returns (for 25th quantile) in 22% can be attributed to investment in bonds with maturity of 5 years. For DWS it is 64.5%. Impact of yields from 10 year bonds on low returns of UNI fund is estimated at 32.8%, whereas for DWS they are negligible. Important differences can be also noticed for these two funds as far as exposition for stock returns is concerned.

The results of style shares analysis obtained from LSM for all funds are given in Table 3. The results for quantile models are collected in Table 4. By analyzing the numbers in the tables one can easily extend previous findings obtained for UNI and DWS funds to other funds.

Table 3. Least squares style shares

Index	AVI	BPH	BZW	DWS	ING	KBC	LEG	MIL	NOV	PIO	PKO	SKA	UNI
WIG-$_{ban}$	0.06	0.13	0.25	0.16	0.20	0.20	0.15	0.10	0.13	0.25	0.10	0.11	0.17
WIG-$_{bud}$	0.07	0.10	0.12	0.09	0.08	0.12	0.05	0.07	0.09	0.06	0.07	0.06	0.09
WIG-$_{inf}$	0.03	0.00	0.07	0.06	0.08	0.03	0.04	0.06	0.06	0.07	0.03	0.10	0.07
WIG-$_{spo}$	0.07	0.09	0.04	0.07	0.07	0.10	0.05	0.07	0.05	0.05	0.07	0.06	0.09
WIG-$_{tel}$	0.09	0.03	0.11	0.07	0.06	0.16	0.11	0.08	0.06	0.08	0.06	0.10	0.08
PS	0.22	0.21	0.17	0.23	0.28	0.29	0.21	0.25	0.30	0.21	0.30	0.24	0.15
DS	0.45	0.44	0.24	0.31	0.22	0.09	0.39	0.38	0.31	0.28	0.37	0.34	0.35

Source: own calculations.

Table 4. Quantile style analysis shares

Order	Index	AVI	BPH	BZW	DWS	ING	KBC	LEG	MIL	NOV	PIO	PKO	SKA	UNI
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0.05	WIG-$_{ban}$	0.04	0.11	0.11	0.06	0.14	0.15	0.08	0.04	0.04	0.26	0.08	0.06	0.11
	WIG-$_{bud}$	0.01	0.02	0.12	0.02	0.05	0.07	0.01	0.02	0.07	0.00	0.00	0.02	0.02
	WIG-$_{inf}$	0.07	0.10	0.13	0.06	0.11	0.08	0.04	0.13	0.09	0.11	0.05	0.12	0.09
	WIG-$_{spo}$	0.06	0.06	0.00	0.03	0.03	0.06	0.04	0.03	0.03	0.00	0.06	0.04	0.09
	WIG-$_{tel}$	0.09	0.08	0.11	0.03	0.10	0.18	0.18	0.10	0.11	0.08	0.04	0.12	0.12
	PS	0.49	0.62	0.53	0.80	0.46	0.47	0.60	0.60	0.66	0.54	0.72	0.60	0.40
	DS	0.25	0.00	0.00	0.00	0.12	0.00	0.07	0.08	0.00	0.01	0.04	0.04	0.16
0.1	WIG-$_{ban}$	0.04	0.11	0.11	0.11	0.15	0.14	0.07	0.04	0.03	0.26	0.08	0.06	0.11
	WIG-$_{bud}$	0.01	0.02	0.06	0.02	0.05	0.07	0.01	0.02	0.10	0.00	0.00	0.02	0.05
	WIG-$_{inf}$	0.06	0.10	0.11	0.12	0.10	0.08	0.03	0.13	0.08	0.11	0.05	0.12	0.10
	WIG-$_{spo}$	0.06	0.07	0.00	0.06	0.03	0.08	0.04	0.03	0.04	0.00	0.06	0.04	0.08
	WIG-$_{tel}$	0.10	0.08	0.07	0.03	0.10	0.18	0.18	0.10	0.11	0.08	0.04	0.12	0.12
	PS	0.44	0.62	0.65	0.65	0.44	0.46	0.58	0.59	0.64	0.52	0.72	0.56	0.23
	DS	0.29	0.00	0.00	0.00	0.14	0.00	0.08	0.09	0.00	0.03	0.05	0.08	0.31
0.25	WIG-$_{ban}$	0.05	0.11	0.20	0.13	0.15	0.15	0.10	0.05	0.05	0.26	0.08	0.10	0.12
	WIG-$_{bud}$	0.03	0.04	0.11	0.04	0.07	0.13	0.05	0.03	0.12	0.01	0.02	0.03	0.07
	WIG-$_{inf}$	0.04	0.07	0.08	0.12	0.09	0.06	0.04	0.11	0.07	0.10	0.05	0.11	0.09
	WIG-$_{spo}$	0.07	0.07	0.00	0.05	0.02	0.07	0.00	0.05	0.04	0.05	0.06	0.05	0.06
	WIG-$_{tel}$	0.11	0.09	0.09	0.02	0.09	0.17	0.16	0.10	0.11	0.08	0.05	0.11	0.11
	PS	0.43	0.57	0.31	0.64	0.37	0.41	0.47	0.42	0.55	0.29	0.68	0.52	0.22
	DS	0.27	0.04	0.20	0.00	0.21	0.00	0.18	0.24	0.07	0.21	0.07	0.09	0.33
0.5	WIG-$_{ban}$	0.06	0.16	0.24	0.22	0.19	0.19	0.10	0.06	0.09	0.27	0.08	0.10	0.11
	WIG-$_{bud}$	0.07	0.07	0.09	0.08	0.09	0.14	0.09	0.06	0.13	0.04	0.07	0.06	0.10
	WIG-$_{inf}$	0.04	0.00	0.07	0.07	0.08	0.04	0.02	0.11	0.05	0.09	0.00	0.10	0.08
	WIG-$_{spo}$	0.06	0.12	0.08	0.10	0.03	0.08	0.01	0.07	0.06	0.03	0.06	0.05	0.06
	WIG-$_{tel}$	0.10	0.07	0.08	0.03	0.08	0.16	0.17	0.09	0.10	0.07	0.05	0.11	0.13
	PS	0.23	0.28	0.25	0.27	0.28	0.17	0.34	0.30	0.38	0.24	0.46	0.36	0.16
	DS	0.45	0.29	0.19	0.23	0.25	0.21	0.27	0.32	0.18	0.25	0.26	0.20	0.36

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0.75	WIG-$_{ban}$	0.12	0.18	0.29	0.24	0.20	0.31	0.15	0.15	0.13	0.27	0.08	0.13	0.16
	WIG-$_{bud}$	0.09	0.10	0.17	0.10	0.09	0.16	0.12	0.07	0.14	0.07	0.09	0.09	0.15
	WIG-$_{inf}$	0.01	0.00	0.03	0.03	0.06	0.01	0.00	0.06	0.02	0.04	0.00	0.07	0.06
	WIG-$_{spo}$	0.08	0.12	0.02	0.10	0.07	0.11	0.00	0.11	0.09	0.07	0.06	0.08	0.03
	WIG-$_{tel}$	0.08	0.06	0.09	0.03	0.09	0.12	0.14	0.07	0.10	0.09	0.06	0.11	0.12
	PS	0.16	0.08	0.12	0.09	0.21	0.04	0.23	0.10	0.25	0.06	0.36	0.23	0.13
	DS	0.47	0.46	0.29	0.41	0.28	0.25	0.36	0.43	0.27	0.39	0.35	0.29	0.35
0.9	WIG-$_{ban}$	0.10	0.18	0.27	0.25	0.21	0.30	0.16	0.15	0.15	0.30	0.10	0.11	0.17
	WIG-$_{bud}$	0.10	0.13	0.21	0.11	0.11	0.18	0.13	0.08	0.15	0.06	0.09	0.12	0.14
	WIG-$_{inf}$	0.00	0.00	0.00	0.02	0.05	0.00	0.00	0.05	0.00	0.02	0.00	0.06	0.03
	WIG-$_{spo}$	0.09	0.12	0.03	0.11	0.09	0.11	0.00	0.15	0.10	0.09	0.09	0.09	0.14
	WIG-$_{tel}$	0.09	0.05	0.10	0.04	0.09	0.14	0.14	0.07	0.10	0.09	0.05	0.10	0.10
	PS	0.02	0.00	0.00	0.00	0.11	0.00	0.10	0.00	0.09	0.01	0.33	0.16	0.00
	DS	0.60	0.53	0.39	0.47	0.33	0.27	0.47	0.49	0.41	0.42	0.35	0.35	0.42
0.95	WIG-$_{ban}$	0.10	0.18	0.40	0.25	0.23	0.31	0.17	0.15	0.15	0.32	0.10	0.12	0.17
	WIG-$_{bud}$	0.11	0.13	0.10	0.11	0.13	0.18	0.13	0.10	0.15	0.08	0.09	0.13	0.14
	WIG-$_{inf}$	0.00	0.00	0.00	0.02	0.04	0.00	0.00	0.06	0.00	0.00	0.00	0.05	0.03
	WIG-$_{spo}$	0.09	0.12	0.03	0.11	0.12	0.12	0.03	0.12	0.10	0.09	0.09	0.09	0.15
	WIG-$_{tel}$	0.08	0.05	0.08	0.04	0.08	0.12	0.12	0.07	0.10	0.08	0.05	0.10	0.10
	PS	0.00	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.09	0.00	0.33	0.17	0.00
	DS	0.62	0.53	0.39	0.47	0.31	0.26	0.55	0.50	0.41	0.43	0.35	0.34	0.42

Source: own calculations.

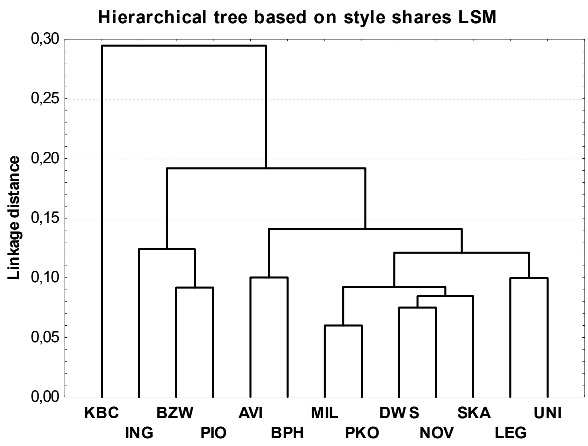

Figure 5. Classification of the PMBF according to style weights estimated by QSA and OLS

Source: own calculations.

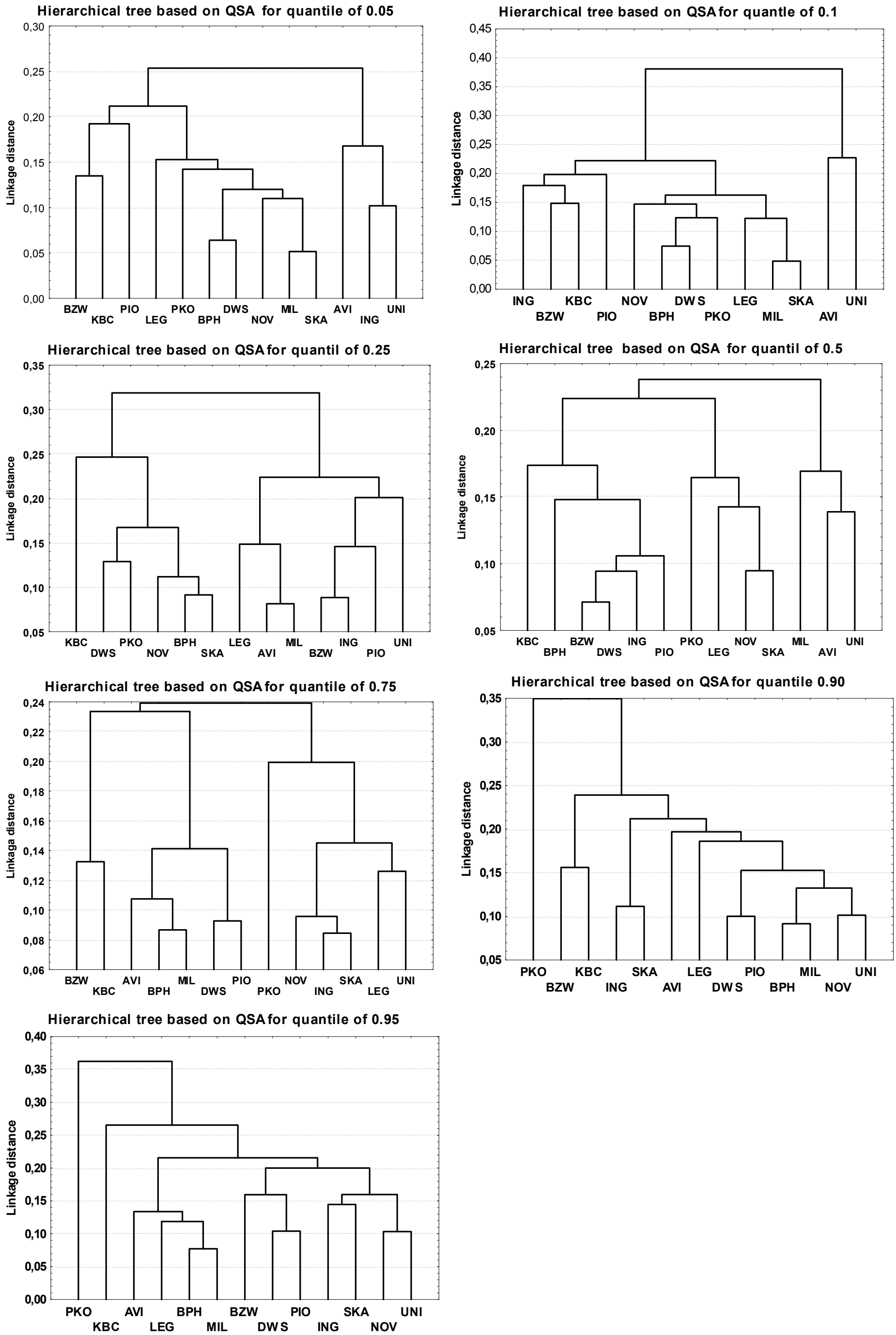

Figure 6. Classification of the PMBF according to style weights estimated by QSA and OLS

Source: own calculations.

In the next stage, classification of the funds was performed according to estimated style shares by the ordinary least squares and from the four different quantile orders.

Figure 5 refers to classification obtained from shares estimated OLS and the next ones to quantile regression. Analysis of the results of classification based on LSM shares reveals significant heterogeneity of funds according to style exposition. This heterogeneity can partially be attributed to the way the balanced fund operates. Their portfolios can consist of up to 69% of shares and the rest is bonds and treasury bills. Since the funds do not conduct strictly homogenous investment policies the returns can be shaped by very different factors (represented by share and bond indices) and differ from returns obtained by other funds.

We compare style shares obtained from LSM with those estimated by quantile style analysis models (Figure 6). Hierarchical trees depict results of the classification using a mean linkages method and Euclidean distance (for a given order of the quantile trees obtained from other distance the measures are similar). Significant differences according to clusters suggest that restricting assessment of the balanced funds heterogeneity only to results obtained from classical style analysis is not justifiable. Style exposition analysis for different quantiles may shed new light on the funds comparisons and classification. It should also be emphasized that there are considerable differences between the style share obtained from the ordinary least squares and those obtained from the quantile regression of order 0.5. They can very likely be attributed to asymmetry of the conditional distribution of participation unit returns.

7. Conclusions

The main advantage of the quantile style analysis comes from its ability to investigate not only the central part of a distribution but also tails. This is very important in the case of asymmetric distributions of returns.

The results of the classification support the thesis on heterogeneity of style expositions calculated for different parts of conditional distribution of returns. For different orders of quantiles different classes of the funds were obtained. Therefore the funds differ in the style exposition for given parts of distribution as well as the expositions vary for different orders of quantiles. Style shares heterogeneity of the balanced mutual funds for different part of conditional distribution of returns does not justify restricting style estimates to the central part of distribution. Moreover classifications obtained for different quantile orders can be very different. These results justify using quantile regression approach to the style analysis of mutual balanced funds. Style exposition analysis for different quantiles may shed new light on the funds comparisons and classification. The decision on which part of the distribution the estimates should be based depend on the aim of the research. For example for risk analysis based on threat measures, the right information can be found in quantiles of the lowest order, especially for the asymmetric distribution case.

More information on a fund management style can be extracted from dynamic quantile style analysis (with variable shares assumption). This problem is left by the authors for further investigation.

References

Kim T., White H., Stone D., Asymptotic and Bayesian confidence intervals for Sharpe-style weights, *Journal of Financial Econometric* 2005, Vol. 3 (3), pp. 315–343.

Koenker R., Basset B., Regression quantiles, *Econometrica* 1978, Vol. 46, pp. 33–50.

Koenker R., Ng P., Inequality constrained quantile regression, *The Indian Journal of Statistics* 2005, Vol. 67, pp. 418–440.

Orwat A., Nieklasyczne metody estymacji przedziałowej wag stylu Sharpe'a na przykładzie modeli analizy stylu zarządzania OFE, [in:] K. Jajuga, W. Ronka-Chmielowiec (Eds.), *Inwestycje finansowe i ubezpieczenia – Tendencje światowe a polski rynek*, Prace Naukowe Akademii Ekonomicznej nr 1197, AE, Wrocław 2008, pp. 302–311.

Orwat A., Bayesian interval estimation of Sharpe style weights in the model of style analysis of the management of Open Pension Funds, *Acta Universitatis Lodziensis Folia Oeconomica*, Vol. 228, Łódź 2009, pp. 61–68.

Orwat A., The classification of Polish mutual balanced funds according to the management style using Andrews estimators, *Studia Ekonomiczne. Statistical Inference Methods in Econometric Research* 2011, 65, pp. 73–89.

Portnoy S., Koenker R., The Gaussian hare and the Laplacian tortoise: Computability of squared-error versus absolute-error estimators, with discussion, *Statistical Science* 1997, Vol. 12.

Sharpe W.F., Asset allocation management style and performance measurement, *Journal of Portfolio Management* 1992, Vol. 18 (2), pp. 7–19.

Trzpiot G., Implementacja metodologii regresji kwantylowej w estymacji VaR, *Studia i Prace Wydziału Nauk Ekonomicznych i Zarządzania*, Vol. 9, US, Szczecin 2008, pp. 316–323.

Trzpiot G., Model regresji kwantylowej a estymacja modelu czynnikowego, [in:] K. Jajuga, W. Ronka--Chmielowiec (Eds.), *Inwestycje finansowe i ubezpieczenia – tendencje światowe a polski rynek*, Prace Naukowe Uniwersytetu Ekonomicznego nr 60, UE, Wrocław 2009a, pp. 469–479.

Trzpiot G., Application weighted VaR in capital allocation, *Polish Journal of Environmental Studies* 2009b, Vol. 18, 5B, Olsztyn, pp. 203–208.

Trzpiot G., Estimation methods for quantile regression, *Studia Ekonomiczne* 53, AE, Katowice 2009c, pp. 81–90.

Trzpiot G., Model regresji kwantylowej relacji stopa zwrotu − zmienność dla wybranych indeksów z GPW w Warszawie, *Finanse, Rynki Finansowe i Ubezpieczenia. Rynek Kapitałowy*, Vol. 28, US, Szczecin 2010, pp. 61–76.

KLASYFIKACJA POLSKICH FUNDUSZY INWESTYCYJNYCH ZRÓWNOWAŻONYCH ZE WZGLĘDU NA STYL ZARZĄDZANIA – PODEJŚCIE REGRESJI KWANTYLOWEJ

Streszczenie: Analiza stylu bada wpływ czynników reprezentujących inwestycje w klasy aktywów na stopy zwrotu funduszu. W przypadku asymetrycznych rozkładów stóp zwrotu stosowanie klasycznej analizy stylu Sharpe'a może prowadzić do błędnego wnioskowania na podstawie współczynników modelu. Kwantylowa analiza stylu bada zależność pomiędzy stopami zwrotu funduszu a czynnikami ryzyka w odniesieniu do kwantyla rozkładu. Celami pracy są badanie wpływu inwestycji w akcje i obligacje na stopy zwrotu jednostek uczestnictwa funduszy inwestycyjnych zrównoważonych za pomocą kwantylowej analizy stylu oraz ocena przydatności podejścia kwantylowego w analizie stylu tych funduszy. Porównujemy struktury oszacowanych współczynników modeli w różnych częściach rozkładu stóp zwrotu oraz klasyfikujemy fundusze względem współczynników modelu oszacowanych klasycznie i kwantylowo.

Słowa kluczowe: kwantylowa analiza stylu, regresja kwantylowa, fundusze inwestycyjne zrównoważone.