

Joanna Olbryś

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ARCH EFFECTS IN MULTIFACTOR MARKET-TIMING MODELS OF POLISH MUTUAL FUNDS

Joanna Olbryś, Ph.D.

*Faculty of Computer Science
Białystok University of Technology
Wiejska 45A, 15-351 Białystok
e-mail: j.olbrys@pb.edu.pl*

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Abstract

Performance measurement of investment managers is a topic of interest to practitioners and academics alike. The traditional performance evaluation literature has attempted to distinguish stock-picking ability (selectivity) from the ability to predict overall market returns (market-timing). However, the literature finds that it is not easy to separate ability into two such dichotomous categories. To overcome these problems multifactor alternative market-timing models have been proposed. The author's recent research provides evidence of strong ARCH effects in the market-timing models of Polish equity open-end mutual funds. For this reason, the main goal of this paper is to present the regression results of the new GARCH(p, q) versions of market-timing models of these funds. We estimate multifactor extensions of classical market-timing models with Fama & French's spread variables SMB and HML, and Carhart's momentum factor WML. We also include lagged values of the market factor as an additional independent variable in the regressions of the models because of the pronounced "Fisher effect" in the case of the main Warsaw Stock Exchange indexes. The market-timing and selectivity abilities of fund managers are evaluated for the period January 2003–December 2010. Our findings suggest that the GARCH(p, q) model is suitable for such applications.

Keywords: market-timing, size, book-to-market, momentum, nonsynchronous trading, ARCH effects, GARCH models.

JEL classification: C1, C32, G1, G2.

Introduction

In 1972 Fama proposed a formalized theoretical methodology for the decomposition of total return into the components of timing and selectivity. Treynor & Mazuy¹ develop a procedure for detecting timing ability that is based on a regression analysis of the managed portfolio's realized returns which includes a quadratic term. Henriksson & Merton² propose a theoretical structure that allows for the formal distinction of managers' forecasting skills into timing and selectivity. By assuming that the market timer's forecasts take two possible predictions: either stocks will outperform bonds or bonds will outperform stocks, Merton derives an equilibrium theory which shows that the return patterns resulting from a market-timing strategy are similar to a return pattern of an option strategy³. Some other researchers develop models that allow the decomposition of managers' performance into market-timing and selectivity skills. The majority of empirical studies seem to suggest that significant positive timing ability is rare.

According to the literature, the method most widely applied in market-timing models estimation is the one proposed by Newey & West in 1987⁴. Some previous publications also describe applications of the GLS procedure with correction for heteroskedasticity⁵ or the Fama-MacBeth cross-sectional regression approach from 1973⁶. Kao et al.⁷ employ an autoregressive conditional heteroskedastic (ARCH) model, but without testing ARCH effects. Recent studies in market-timing models in the case of Polish equity funds by Olbryś present possibilities and examples of applying the seemingly unrelated regression method (SUR) which was described by Zellner⁸.

The author's recent research provides evidence of strong ARCH effects⁹ in the market-timing models of Polish equity open-end mutual funds. For this reason, the main goal of this paper is to present the regression results of the new GARCH(p, q) versions of market-timing models of these selected funds. We estimate multifactor extensions of classical market-timing models with Fama & French's spread variables SMB and HML, and Carhart's momentum factor WML. We also include lagged values of the market factor as an additional independent variable in the regressions of the models because of the pronounced "Fisher effect" in the case of the main Warsaw Stock Exchange indexes. The market-timing and selectivity abilities of funds' managers are evaluated for the period January 2003–December 2010. Our findings suggest that the GARCH(p, q) model is suitable for such applications.

The remainder of the paper is organized as follows. Section 1 specifies a methodological framework and a brief literature review. First, we stress a validity of nonsynchronous security trading problem. Next, we present multifactor extensions of classical market-timing models

with stock characteristics as additional explanatory variables. We also present a brief theoretical background concerning the ARCH(q) and the GARCH(p, q) models. In the end of Section 1, we describe tests for the ARCH effect in an econometric model. In Section 2, we present the data and methodology in the case of Polish market and discuss the results obtained. Section 3 recalls the main findings and presents conclusions.

1. Methodological Framework

1.1. Nonsynchronous Security Trading Problem and the “Fisher Effect”

The empirical market microstructure literature is an extensive one. High-frequency financial data are important in studying a variety of issues related to the trading process and market microstructure¹⁰. For some purposes, such aspects of the market microstructure as nonsynchronous trading or bid-ask spread effects can be safely ignored, particularly when longer investment horizons are involved. However, for other purposes, market microstructure is central¹¹. In 1980 Cohen et al. point to various frictions in the trading process that can lead to a distinction between “true” and observed returns. They have focused on the fact that transaction prices differ from what they would otherwise be in a frictionless environment. It has been reported in the literature that some empirical phenomena can be attributed to frictions in the trading process¹². Two common elements among most of the phenomena are evident, the intervaling effect and the impact of a security’s “thinness”. In 1970 Fama found slightly positive average serial correlations in daily security returns with a lag of one day and no empirical evidence of significant serial correlations for higher lags. Scholes & Williams show how nonsynchronous security trading will induce spurious auto- and cross-correlations into individual security and market index returns¹³. Cohen et al.¹⁴ place nonsynchronous trading in a broader class of market frictions, which may induce price-adjustment delays into the trading process¹⁵. The evidence that daily market-index returns exhibit a pronounced positive first-order autocorrelation has been called the “Fisher effect” since Lawrence Fisher in 1966 hypothesized its probable cause. Fisher suggested it was caused by a nonsynchronous trading of the component securities. The observed correlation is higher in those indexes that give greater weight to the securities of smaller firms.

The nontrading effect induces potentially serious biases in the moments and co-moments of asset returns such as their means, variances, covariances, betas, and autocorrelation and cross-autocorrelation coefficients¹⁶. For this reason, Busse proposed lagged values of the market factor as an additional independent variable in the regressions of market-timing models using Dimson’s correction¹⁷.

1.2. Multifactor Market-Timing Model with Lagged Market Variable

In 1992 Fama and French documented that two variables, the market value (MV) and the book value to market value ratio (BV/MV) capture much of the cross-section of average stock returns. In 1993, Fama & French formed portfolios meant to mimic the underlying risk factors in returns related to size and book-to-market equity. These mimicking SMB (Small-minus-Big) and HML (High-minus-Low) portfolios on the Polish market have been constructed by Olbryś, using the Fama & French's¹⁸ procedure. The SMB factor measures the performance of small stocks relative to large stocks. The HML factor measures the performance of value stocks relative to growth stocks.

In 1993 Jegadeesh & Titman documented a pronounced one-year momentum anomaly in stock returns. Rouwenhorst documents an international return continuation in a sample of 12 European countries (Austria, Belgium, Denmark, France, Germany, Italy, The Netherlands, Norway, Spain, Sweden, Switzerland and the UK)¹⁹. The European evidence is remarkably similar to findings for the U.S. by Jegadeesh & Titman. In 2005 Buczek showed that a momentum phenomena probably exists on the Warsaw Stock Exchange. Carhart constructs a four-factor model using the Fama & French's factors plus an additional factor capturing Jegadeesh's & Titman's one-year momentum anomaly to explain the portfolio returns of the mutual funds. The momentum factor WML (Winners-minus-Losers) on the Polish market has been constructed by Olbryś, using the Carhart's procedure²⁰.

In the new modified multifactor Treynor-Mazuy model with the Fama & French spread variables SMB and HML, and the C-momentum variable WML, and with the lagged market factor (T-M-FF-C model) has been expressed as²¹:

$$r_{P,t} = \alpha_P + \beta_{1P} \cdot r_{M,t} + \beta_{2P} \cdot r_{M,t-1} + \delta_{1P} \cdot r_{SMB,t} + \delta_{2P} \cdot r_{HML,t} + \delta_{3P} \cdot r_{WML,t} + \gamma_P \cdot (r_{M,t})^2 + \varepsilon_{P,t} \quad (1)$$

where:

$R_{P,t}$ is the one-period return on portfolio P ,

$R_{M,t}$ is the one-period return on market portfolio M ,

$R_{F,t}$ is the one-period return on riskless securities,

$r_{P,t} = R_{P,t} - R_{F,t}$ is the excess return on portfolio P in the period t ,

$r_{M,t} = R_{M,t} - R_{F,t}$ is the excess return on portfolio M in the period t ,

$r_{M,t-1}$ is the lagged excess return on portfolio M in the period t ,

$r_{SMB,t} = R_{SMB,t} - R_{F,t}$ is the excess return on the mimicking portfolio SMB in the period t ,

$r_{HML,t} = R_{HML,t} - R_{F,t}$ is the excess return on the mimicking portfolio HML in the period t ,

$r_{WML,t} = R_{WML,t} - R_{F,t}$ is the excess return on the mimicking portfolio WML in the period t ,
 Jensen's α_p measures the selectivity skills of the manager of portfolio P^{22} ,
 β_{1P} is the systematic risk measure of portfolio P to changes in the market factor returns,
 β_{2P} is the systematic risk measure of portfolio P to changes in the lagged market factor returns,
 δ_{1P} is the sensitivity measure of the returns on portfolio P to changes in the SMB factor returns,
 δ_{2P} is the sensitivity measure of the returns on portfolio P to changes in the HML factor returns,
 δ_{3P} is the sensitivity measure of the returns on portfolio P to changes in the WML factor returns,
 γ_P measures the market-timing skills of the manager of portfolio P ,
 $\varepsilon_{P,t}$ is a residual term, with the following standard $CAPM$ conditions: $E(\varepsilon_{P,t}) = 0$, $E(\varepsilon_{P,t}|\varepsilon_{P,t-1}) = 0$.

In a way analogous to (1), Olbryś expressed the new modified multifactor Henriksson-Merton model with the FF-spread variables SMB and HML , and the C-momentum variable WML , and with the lagged market factor (H-M-FF-C model) as²³:

$$\begin{aligned}
 r_{P,t} = & \alpha_P + \beta_{1P} \cdot r_{M,t} + \beta_{2P} \cdot r_{M,t-1} + \delta_{1P} \cdot r_{SMB,t} + \\
 & + \delta_{2P} \cdot r_{HML,t} + \delta_{3P} \cdot r_{WML,t} + \gamma_P \cdot y_{M,t} + \varepsilon_{P,t}
 \end{aligned} \tag{2}$$

where: $r_{P,t}$, $r_{M,t}$, $r_{M,t-1}$, $r_{SMB,t}$, $r_{HML,t}$, $r_{WML,t}$, α_P , β_{1P} , β_{2P} , δ_{1P} , δ_{2P} , δ_{3P} , γ_P , $\varepsilon_{P,t}$ are as in equation (1) and $y_{M,t} = \max\{0, -r_{M,t}\}$.

If the portfolio manager has the ability to forecast security prices, the intercept α_p in equations (1)–(2) will be positive²⁴. Indeed, it represents the average incremental rate of return on the portfolio per unit time which is due solely to the manager's ability to forecast future security prices. In this way, $\hat{\alpha}_p$ measures the contribution of security selection to portfolio performance, which corresponds to testing the null hypothesis:

$$H_0 : \alpha_p = 0 \tag{3}$$

i.e., the manager does not have any micro-forecasting ability.

The evaluation of market-timing skills is carried out by testing the null hypothesis:

$$H_0 : \gamma_p = 0 \tag{4}$$

i.e., the manager does not possess any timing ability or does not on his forecast²⁵. A negative value for the regression estimate \hat{y}_p would imply a negative value for market-timing. The size of the estimate \hat{y}_p informs us about the manager's market skills.

1.3. The GARCH(p, q) Model

The ARCH(q) regression model is obtained by assuming that the mean of random variable y_t , which is drawn from the conditional density function $f(y_t|y_{t-1})$, is given as $x_t b$, a linear combination of lagged endogenous and exogenous variables included in the information set Ψ_{t-1} , with b a vector of unknown parameters²⁶. Formally,

$$\begin{aligned} y_t | \Psi_{t-1} &\sim N(x_t b, h_t), \\ \varepsilon_t &= y_t - x_t b, \\ h_t &= h(\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-q}, \alpha) = \alpha_0 + \sum_{i=1}^q \alpha_i \cdot \varepsilon_{t-i}^2, \quad \alpha_0 > 0, \alpha_i \geq 0, i = 1, \dots, q \end{aligned} \quad (5)$$

where:

ε_t is the innovation in a linear regression with $V(\varepsilon) = \sigma^2$,

q is the order of the ARCH(q) process,

α is the vector of unknown parameters,

h_t is the variance function.

The null hypothesis of white noise disturbances in (5) is:

$$H_0 : \alpha_1 = \dots = \alpha_q = 0 \quad (6)$$

The GARCH(p, q) model generalizes the ARCH(q) model of Engle and is proposed by Bollerslev²⁷. The GARCH(p, q) is given by:

$$\begin{aligned} y_t | \Psi_{t-1} &\sim N(x_t b, h_t), \\ \varepsilon_t &= y_t - x_t b, \\ h_t &= h(\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-q}, h_{t-1}, h_{t-2}, \dots, h_{t-p}, \alpha, \beta) = \\ &= \alpha_0 + \sum_{i=1}^q \alpha_i \cdot \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \cdot h_{t-j}, \\ \alpha_0 &> 0, \quad \alpha_i \geq 0, i = 1, \dots, q, \quad q > 0, \quad \beta_j \geq 0, j = 1, \dots, p, \quad p \geq 0 \end{aligned} \quad (7)$$

where: ε_t , q , α , h_t are as in equation (5) and β is a vector of unknown parameters.

In the GARCH(p, q) model, q refers to the number of lags of ε_t and p refers to the number of lags of h_t to include in the model of the regression variance²⁸. For $p = 0$ the process reduces to the ARCH(q) process, and for $p = q = 0$, ε_t is simple white noise.

The null hypothesis of white noise disturbances in (7) is:

$$H_0 : \alpha_1 = \dots = \alpha_q = 0; \beta_1 = \dots = \beta_p = 0 \quad (8)$$

In the ARCH(q) process the conditional variance is specified as a linear function of past sample variances only, whereas the GARCH(p, q) process allows lagged conditional variances to enter as well²⁹. A wide range of GARCH models have now appeared in the econometric literature³⁰.

The parameters of GARCH(p, q) models are almost invariably estimated via Maximum Likelihood (ML) or Quasi-Maximum Likelihood (QML)³¹ methods, which bring up the subject of a suitable choice for the conditional distribution of ε_t . Several likelihood functions are commonly used in ARCH (GARCH) estimation, depending on the distributional assumption of ε_t ³².

1.4. Testing for ARCH Effect in an Econometric Model

Before estimating the GARCH(p, q) model it might be useful to test for ARCH (or GARCH) effects. The simplest approach is to examine the squares of the least squares residuals. The autocorrelations of the squares of the residuals provide evidence about ARCH effects³³. Two tests are available. The first test is to apply the Ljung-Box statistics $Q(q)$ ³⁴. The null hypothesis is that the first q lags of ACF of the squares of the least squares residuals series are zero. In practice, the choice of q may affect the performance of the $Q(q)$ statistic. Simulation studies suggest that the choice of $q \approx \ln(T)$, where T is the number of time periods, provides better power performance³⁵. The second test for conditional heteroskedasticity is the Lagrange multiplier (LM) test of Engle³⁶. Lee found that the LM test of white noise disturbances against GARCH(p, q) disturbances in a linear regression model is equivalent to that against ARCH(q) disturbances. Hence we can proceed by testing the ARCH(q) effect against the GARCH(p, q) effect³⁷.

An LM test of ARCH(q) against the hypothesis of no ARCH effects can be carried out by computing $\chi^2_q = T \cdot R^2$, where R^2 is the determination coefficient of the estimated econometric model. Under the null hypothesis (6), the statistic has a limiting chi-squared distribution with q degrees of freedom. Values larger than the critical table value give evidence of the presence of ARCH (or GARCH) effects³⁸.

2. Data and Empirical Results

2.1. The “Fisher Effect” on the Warsaw Stock Exchange

To detect for the “Fisher effect” on the Warsaw Stock Exchange (WSE) in the period investigated January 2, 2003 – December 31, 2010 (2013 observations), daily logarithmic returns on the WSE indexes: WIG, WIG20, mWIG40 and sWIG80 have been studied.

The whole sample has been divided into seven samples: P1, P2, P3, P4, P5, P6, P7 (see Table 1). In the next step partial autocorrelations functions (PACF) have been calculated. To calculate partial autocorrelations functions (PACF), first it has been determined (based on the ADF test) that the analyzed series: WIG, WIG20, mWIG40, and sWIG80 are stationary. Empirical values of the τ -statistic (at the 5% significance level) lie in the $[-32.59; -26.97]$ interval and they are substantially lower than the critical value equal to -3.41 . In the next step partial autocorrelations functions for individual stationary processes, in the seven samples P1, P2, P3, P4, P5, P6, P7 have been calculated and the significance of the first-order daily serial correlation coefficients ρ_1 has been tested, using the Quenouille’s test. The critical value of the Quenouille’s test is equal to $\frac{u_\alpha}{\sqrt{n}} = \frac{1.96}{\sqrt{n}}$. The evaluation of first-order serial correlation is carried out by testing the null hypothesis:

$$H_0 : \rho_1 = 0 \quad (9)$$

Table 1. PACF estimators of the WSE indexes (first-order daily serial correlation)

	Quenouille’s test	WIG	WIG20	mWIG40	sWIG80
Sample P1 Jan 2, 2003-Dec 31, 2010	0.044	0.091	0.044	0.187	0.233
Sample P2 Jan 2, 2004-Dec 31, 2010	0.047	0.089	0.041	0.186	0.216
Sample P3 Jan 3, 2005-Dec 31, 2010	0.050	0.090	0.040	0.185	0.201
Sample P4 Jan 2, 2006-Dec 31, 2010	0.055	0.088	0.035	0.186	0.205
Sample P5 Jan 2, 2007-Dec 31, 2010	0.062	0.088	0.035	0.179	0.183
Sample P6 Jan 2, 2008-Dec 31, 2010	0.071	0.101	0.044	0.224	0.245
Sample P7 Jan 5, 2009-Dec 31, 2010	0.087	0.111	0.066	0.186	0.189

Notes: The table is based on the whole sample P1 and six subsamples P2- P7.

We study daily logarithmic returns on the Warsaw Stock Exchange indexes: WIG, WIG20, mWIG40 and sWIG80.

Source: Author’s calculations (using *Gretl 1.9.5*).

If the estimate $\hat{\rho}_1$ satisfies the inequality $|\hat{\rho}_1| \leq \frac{1.96}{\sqrt{n}}$, then we have no reason to reject the null hypothesis (9). Table 1 provides details on the first-order daily serial correlations in the analyzed series.

The empirical results show a pronounced “Fisher effect” in the case of the WIG, mWIG40, and sWIG80 series. We observe the most clear effect for the sWIG80 series. We have no reason to reject the null hypothesis (9) only in the case of the WIG20 series. This evidence is consistent with most of the literature on frictions in the trading process. For the “Fisher effect” reason, we could use Dimson’s correction and include lagged values of the market factor (i.e. the main index of WSE companies – WIG) as an additional independent variable in the regressions of market-timing models of Polish equity open-end mutual funds to accommodate infrequent trading³⁹.

2.2. Data: the Case of Polish Equity Open-End Mutual Funds

The creation of investment funds in Poland was made possible by the legislative act of March 22, 1991. The first balanced open-end mutual fund Pioneer was created in 1992. It was the only open-end investment fund until 1995, when it was joined by the stable growth open-end mutual fund Korona. The first equity open-end mutual fund Pioneer was created in 1995. A proliferation of funds in Poland was made possible by the legislative act of August 28, 1997. For this reason, we have examined the performance of 15 selected equity open-end

Table 2. Equity open-end mutual funds in Poland by the end of 2002

	Equity funds (current names)	Short Name	Abbreviation	Year of creation
1	Arka BZ WBK FIO Subfundusz Arka Akcji FIO	Arka	ARDS	1998
2	Aviva Investors FIO Subfundusz Aviva Investors Polskich Akcji	Aviva	CUPA	2002
3	BPH FIO Parasolowy BPH Subfundusz Akcji	BPH	CARS	1999
4	ING Parasol FIO ING Subfundusz Akcji	ING	INGA	1998
5	Investor Top 25 Małych Spółek FIO	Investor 25	D25M	2002
6	Investor Akcji Dużych Spółek FIO	Investor ADS	DWAK	1998
7	Investor Akcji FIO	Investor	DWA+	1998
8	Legg Mason Akcji FIO	Legg Mason	KH2A	1999
9	Millennium FIO Subfundusz Akcji	Millennium	MIAK	2002
10	Novo FIO Subfundusz Novo Akcji	Novo	SEB3	1998
11	Pioneer FIO Subfundusz Pioneer Akcji Polskich	Pioneer	PIO3	1995
12	PKO Akcji - FIO	PKO	PKCA	1998
13	PZU FIO Parasolowy Subfundusz PZU Akcji Krakowiak	PZU	PZUK	1999
14	Skarbiec FIO Subfundusz Akcji Skarbiec – Akcja	Skarbiec	SKAA	1998
15	UniFundusze FIO Subfundusz UniKorona Akcje	UniKorona	UNIA	1997

Source: Polish Financial Supervision Authority <http://www.knf.gov.pl>.

Polish mutual funds which were created up to the end of 2002. Our dataset includes returns on all the equity funds in existence in Poland from 2002 to 2010, therefore our results are free of survivorship bias. Due to this fact the period investigated was determined as from January 2, 2003 to December 31, 2010.

We have studied daily logarithmic excess returns. Daily returns on the main index of Warsaw Stock Exchange companies are used as the returns on the market portfolio. The daily average of returns on 52-week Treasury bills are used as the returns on riskless assets. Daily returns on factors SMB, HML and WML are used as the values of the additional exogenous variables in the T-M-FF-C (1) and H-M-FF-C (2) models. As mentioned above, for the “Fisher effect” reason, we include lagged values of the market factor as an additional independent variable.

2.3. ARCH Effects in Multifactor Market-Timing Models of Polish Equity Mutual Funds

To detect for the ARCH(q) effects in market-timing models of Polish equity open-end mutual funds’ portfolios in the period investigated January 2, 2003 – December 31, 2010 ($T = 2013$ observations), the LM (Lagrange Multiplier) and the LB (Ljung-Box) tests have been applied. The empirical results presented in Table 3 show strong ARCH effects in the case of all of the funds. The null hypothesis (6) is rejected in these cases. Because we are using daily logarithmic excess returns on funds’ portfolios, the LM test at the lag $q = 5$ has been applied. On the other hand, the LB test at the lag $q \approx \ln(2013) \approx 8$ has been used⁴⁰. The p values of all statistics are very close to zero.

Table 3. ARCH(q) effects in market-timing models (1) and (2) of Polish equity mutual funds in the period from Jan 2, 2003 to Dec 31, 2010

	Equity funds (short names)	T-M-FF-C model (1)				H-M-FF-C model (2)			
		LM	p-value	LB	p-value	LM	p-value	LB	p-value
1	2	3	4	5	6	7	8	9	10
1	Arka	314.76	$7 \cdot 10^{-66}$	151.40	$1 \cdot 10^{-28}$	335.26	$3 \cdot 10^{-70}$	153.03	$5 \cdot 10^{-29}$
2	Aviva	231.93	$4 \cdot 10^{-48}$	292.60	$2 \cdot 10^{-58}$	233.10	$2 \cdot 10^{-48}$	299.86	$4 \cdot 10^{-60}$
3	BPH	385.21	$5 \cdot 10^{-81}$	409.08	$2 \cdot 10^{-83}$	387.52	$1 \cdot 10^{-81}$	411.58	$6 \cdot 10^{-84}$
4	ING	398.17	$7 \cdot 10^{-84}$	414.13	$2 \cdot 10^{-84}$	399.40	$4 \cdot 10^{-84}$	416.16	$6 \cdot 10^{-85}$
5	Investor 25	417.44	$5 \cdot 10^{-88}$	208.55	$1 \cdot 10^{-40}$	406.09	$1 \cdot 10^{-85}$	205.77	$4 \cdot 10^{-40}$
6	Investor ADS	487.35	$4 \cdot 10^{-103}$	442.77	$1 \cdot 10^{-90}$	493.91	$2 \cdot 10^{-104}$	442.27	$2 \cdot 10^{-90}$
7	Investor	431.52	$5 \cdot 10^{-91}$	462.05	$1 \cdot 10^{-94}$	431.60	$5 \cdot 10^{-91}$	460.74	$2 \cdot 10^{-94}$
8	Legg Mason	355.15	$1 \cdot 10^{-74}$	313.84	$5 \cdot 10^{-63}$	361.56	$6 \cdot 10^{-76}$	314.97	$3 \cdot 10^{-63}$
9	Millennium	392.57	$1 \cdot 10^{-82}$	351.91	$3 \cdot 10^{-71}$	394.61	$4 \cdot 10^{-83}$	355.02	$8 \cdot 10^{-72}$
10	Novo	581.94	$2 \cdot 10^{-123}$	442.48	$1 \cdot 10^{-90}$	572.23	$2 \cdot 10^{-121}$	438.50	$1 \cdot 10^{-89}$

1	2	3	4	5	6	7	8	9	10
11	Pioneer	388.69	$8 \cdot 10^{-82}$	356.96	$3 \cdot 10^{-72}$	391.27	$2 \cdot 10^{-82}$	359.45	$9 \cdot 10^{-73}$
12	PKO	448.11	$1 \cdot 10^{-94}$	351.27	$5 \cdot 10^{-71}$	439.67	$8 \cdot 10^{-93}$	351.40	$5 \cdot 10^{-71}$
13	PZU	357.43	$4 \cdot 10^{-75}$	359.83	$7 \cdot 10^{-73}$	360.34	$1 \cdot 10^{-75}$	364.93	$6 \cdot 10^{-74}$
14	Skarbiec	339.64	$3 \cdot 10^{-71}$	398.89	$3 \cdot 10^{-81}$	341.47	$1 \cdot 10^{-71}$	398.21	$4 \cdot 10^{-81}$
15	UniKorona	341.24	$1 \cdot 10^{-71}$	481.07	$8 \cdot 10^{-99}$	344.68	$2 \cdot 10^{-72}$	480.46	$1 \cdot 10^{-98}$

Notes: The table is based on the whole sample P1.

The T-M-FF-C (1) is the modified version of the Treynor-Mazuy model with the FF-spread variables (SMB and HML), the C-momentum variable (WML) and the lagged excess return on market portfolio M as additional factors.

The H-M-FF-C (2) is the modified version of the Henriksson-Merton model with the FF-spread variables (SMB and HML), the C-momentum variable (WML) and the lagged excess return on market portfolio M as additional factors.

LM is the Engle (1982) statistic at the lag equal to five, which should be distributed as χ^2_5 .

LB is the Ljung-Box (1978) statistic at the lag equal to eight, which should be distributed as χ^2_8 .

Source: Author's calculations (using *Gretl 1.9.5*).

2.4. The GARCH(p, q) Versions of Market-Timing Models of Polish Equity Mutual Funds

The testing results from the Polish equity mutual funds dataset show pronounced ARCH effects in market-timing models (Table 3). For this reason, the estimation of the market-timing models as the GARCH(p, q) models is well-founded. Although the ARCH(q) model (5) is simple, it often requires many parameters to adequately describe the volatility process. The modeling procedure of the ARCH(q) model can also be used to build a GARCH(p, q) model (7). However, specifying the order of a GARCH(p, q) model is not easy. Only lower order GARCH models are used in most applications, i.e. GARCH(1,1), GARCH(1,2), and GARCH(2,1) models⁴¹. According to the literature, GARCH(p, q) models are usually compared and selected by the information criterion of Akaike (AIC) and the information criterion of Schwartz (SC). Lower values of the AIC and SC indexes indicate the preferred model, that is, the one with the fewest parameters that still provides an adequate fit to the data. Tables 4 and 5 (respectively) present the empirical results of selecting the GARCH(p, q) versions of the market-timing models (1) and (2) of Polish equity mutual funds in the period from Jan 2, 2003 to Dec 31, 2010, based on the AIC and the SC criteria.

Table 4. Diagnostic tests for GARCH(p, q) versions of the T-M-FF-C market-timing models (1) of Polish equity mutual funds in the period from Jan 2, 2003 to Dec 31, 2010

	Equity funds (short names)	T-M-FF-C model (1)					
		GARCH(1,1)		GARCH(1,2)		GARCH(2,1)	
		AIC	SC	AIC	SC	AIC	SC
1	2	3	4	5	6	7	8
1	Arka	-15141.08	-15085.00	-15143.15	-15081.47	-15142.48	-15080.79
2	Aviva	-16623.99	-16567.91	-16650.42	-16588.74	-16646.03	-16584.35

1	2	3	4	5	6	7	8
3	BPH	-17511.47	-17455.40	-17515.75	-17454.07	-17515.96	-17454.28
4	ING	-17155.81	-17099.73	-17154.54	-17092.86	-17157.73	-17096.04
5	Investor 25	-14252.24	-14196.16	-14259.20	-14197.52	-14253.70	-14192.01
6	Investor ADS	-13626.99	-13570.92	-13657.49	-13595.81	-13641.63	-13579.94
7	Investor	-14118.76	-14062.69	-14178.16	-14116.47	-14148.30	-14086.62
8	Legg Mason	-16780.11	-16724.04	-16788.52	-16726.84	-16789.49	-16727.81
9	Millennium	-17072.37	-17016.29	-17072.87	-17011.19	-17074.85	-17013.17
10	Novo	-14334.85	-14278.77	-14379.15	-14317.47	-14364.71	-14303.03
11	Pioneer	-16764.74	-16708.69	-16765.65	-16703.97	-16767.84	-16706.16
12	PKO	-14534.29	-14478.22	-14559.97	-14498.29	-14554.50	-14492.82
13	PZU	-17020.35	-16964.27	-17024.84	-16963.16	-17021.59	-16959.91
14	Skarbiec	-14137.40	-14081.33	-14159.74	-14098.05	-14150.37	-14088.69
15	UniKorona	-14001.24	-13945.17	-14028.52	-13966.84	-14015.53	-13953.85

Notes: The table is based on the whole sample P1.

The T-M-FF-C (1) is the modified version of the Treynor-Mazuy model with the FF-spread variables (SMB and HML), the C-momentum variable (WML) and the lagged excess return on market portfolio M as additional factors.

AIC is the information criterion of Akaike (1973).

SC is the information criterion of Schwartz (1978).

Source: Author's calculations (using *Gretl 1.9.5*).

Table 5. Diagnostic tests for GARCH(p, q) versions of the H-M-FF-C market-timing models (2) of Polish equity mutual funds in the period from Jan 2, 2003 to Dec 31, 2010

	Equity funds (short names)	H-M-FF-C model (2)					
		GARCH(1,1)		GARCH(1,2)		GARCH(2,1)	
		AIC	SC	AIC	SC	AIC	SC
1	Arka	-15136.26	-15080.19	-15137.54	-15075.86	-15136.95	-15075.27
2	Aviva	-16480.91	-16424.84	-16513.42	-16451.73	-16500.41	-16438.73
3	BPH	-17510.75	-17454.68	-17515.12	-17453.44	-17515.40	-17453.72
4	ING	-17154.33	-17098.26	-17153.12	-17091.44	-17155.96	-17094.28
5	Investor 25	-14252.33	-14196.25	-14258.40	-14196.72	-14253.48	-14191.80
6	Investor ADS	-13629.47	-13573.40	-13658.68	-13597.00	-13643.94	-13582.26
7	Investor	-14118.92	-14062.85	-14178.21	-14116.53	-14148.41	-14086.73
8	Legg Mason	-16779.69	-16723.62	-16788.27	-16726.59	-16789.13	-16727.45
9	Millennium	-17072.06	-17015.99	-17072.48	-17010.80	-17074.51	-17012.83
10	Novo	-14340.53	-14284.46	-14382.92	-14321.24	-14369.75	-14308.07
11	Pioneer	-16763.98	-16707.90	-16764.59	-16702.91	-16766.84	-16705.16
12	PKO	-14534.20	-14478.12	-14559.97	-14498.29	-14554.28	-14492.59
13	PZU	-17023.11	-16967.04	-17027.60	-16965.92	-17024.32	-16962.64
14	Skarbiec	-14139.13	-14083.05	-14161.30	-14099.62	-14151.91	-14090.22
15	UniKorona	-14003.02	-13946.95	-14030.18	-13968.50	-14017.07	-13955.39

Notes: The table is based on the whole sample P1.

The H-M-FF-C (2) is the modified version of the Henriksson-Merton model with the FF-spread variables (SMB and HML), the C-momentum variable (WML) and the lagged excess return on market portfolio M as additional factors.

AIC is the information criterion of Akaike (1973).

SC is the information criterion of Schwartz (1978).

Source: Author's calculations (using *Gretl 1.9.5*).

The robust quasi-maximum likelihood estimates⁴² of the parameters of the suitable GARCH(p, q) version of the market-timing model (based on Tables 4 and 5) are presented in Table 6 (the T-M-FF-C model (1)) and in Table 7 (the H-M-FF-C model (2)). It is worth stressing that some restrictions for the parameters in the GARCH(p, q) models (7) can be relaxed. For example, it is not necessary for the α_2 parameter in the conditional variance equation in the GARCH(1,2) model to be nonnegative⁴³.

In Tables 6–7 the heteroskedastic consistent standard errors are in the parentheses below the coefficient estimates. The variance-covariance matrix of the estimated parameters is based on the QML⁴⁴ algorithm. The distribution for the innovations ε_t is supposed to be normal. Note that in the case of all funds, both for T-M-FF-C model (1) and for H-M-FF-C model (2) the same variant of the GARCH(p, q) model has been chosen. When the values of the information criteria AIC or SC for different variants of the GARCH(p, q) models in Tables 4 and 5, respectively are almost equal, the statistical significance of the parameters in the conditional mean and conditional variance equations of the GARCH(p, q) model has been analyzed to choose the appropriate model.

2.5. Results and Discussion

Several empirical results in Tables 6-7 are worth special notice. First, the selected GARCH(p, q) models are adequate for describing the conditional heteroskedasticity of the data at the appropriate significance level. Furthermore, based on the conditional mean equation in the GARCH(p, q) model we are able to interpret the estimated coefficients. The estimates of Jensen's performance measure ($\hat{\alpha}_p$) are not significant for almost all of the funds, i.e., the null hypothesis (3) is not rejected. We can observe that the levels of systematic risks ($\hat{\beta}_{1p}$ and $\hat{\beta}_{2p}$) are significantly positive (except for two funds: ING and BPH in the case of $\hat{\beta}_{2p}$). The evidence is that the regressions including lagged values of the market factor $r_{M,t-1}$ as an additional independent variable are well-founded.

As for the influence of the size (SMB), book-to-market (HML) and momentum (WML) factors, it is different, but not controversial. The evidence is that the size factor influence is comparable to the book-to-market factor influence. The number of statistically significant coefficients of the SMB variable ($\hat{\delta}_{1p}$) fluctuates between eleven (Table 6) and twelve (Table 7). The SMB measures the performance of small stocks relative to large stocks. On the other hand, the number of statistically significant coefficients of the HML variable ($\hat{\delta}_{2p}$) fluctuates between thirteen (Table 6) and eleven (Table 7). The HML measures the performance of value stocks relative to growth stocks⁴⁵. Moreover, the results presented in Tables 6–7 show that

Table 6. GARCH(p, q) versions of the T-M-FF-C market-timing models (1) of Polish equity mutual funds (from Jan 2, 2003 to Dec 31, 2010)

Equity fund	T-M-FF-C model (1) – conditional mean equation						Conditional variance equation						
	$\hat{\alpha}_p$	$\hat{\beta}_{1p}$	$\hat{\beta}_{2p}$	$\hat{\delta}_{1p}$	$\hat{\delta}_{2p}$	$\hat{\delta}_{3p}$	$\hat{\gamma}_p$	GARCH(p, q)	$\hat{\omega}_0$	$\hat{\alpha}_i$	$\hat{\omega}_2$	$\hat{\beta}_1$	$\hat{\beta}_2$
1 Arka	0.0004 (0.0001)	0.811 (0.010)	0.041 (0.010)	0.058 (0.011)	0.024 (0.009)	0.016 (0.011)	-1.184 (0.522)	(1,1)	$2 \cdot 10^{-7}$ ($1 \cdot 10^{-7}$)	0.09 (0.02)	–	0.91 (0.02)	–
2 Aviva	0.0003 ($8 \cdot 10^{-5}$)	0.869 (0.010)	0.014 (0.005)	0.031 (0.006)	0.014 (0.005)	0.023 (0.005)	-1.791 (0.343)	(1,2)	$2 \cdot 10^{-7}$ ($6 \cdot 10^{-8}$)	0.47 (0.13)	-0.26 (0.13)	0.82 (0.03)	–
3 BPH	$-7 \cdot 10^{-5}$ ($6 \cdot 10^{-5}$)	0.839 (0.006)	0.006 (0.004)	0.016 (0.004)	0.007 (0.005)	0.011 (0.005)	0.131 (0.178)	(1,2)	$6 \cdot 10^{-8}$ ($2 \cdot 10^{-8}$)	0.15 (0.03)	-0.07 (0.03)	0.92 (0.01)	–
4 ING	-0.0001 ($6 \cdot 10^{-5}$)	0.899 (0.006)	0.002 (0.005)	0.017 (0.008)	0.004 (0.007)	0.010 (0.005)	0.205 (0.223)	(1,1)	$7 \cdot 10^{-8}$ ($2 \cdot 10^{-8}$)	0.08 (0.01)	–	0.91 (0.01)	–
5 Investor 25	$2 \cdot 10^{-5}$ (0.0002)	0.407 (0.024)	0.246 (0.023)	0.168 (0.022)	0.109 (0.019)	0.017 (0.013)	-0.411 (0.850)	(1,2)	$1 \cdot 10^{-6}$ ($8 \cdot 10^{-7}$)	0.28 (0.06)	-0.14 (0.08)	0.85 (0.06)	–
6 Investor ADS	-0.0002 (0.0002)	0.546 (0.084)	0.415 (0.067)	-0.003 (0.018)	0.057 (0.015)	0.009 (0.015)	-0.122 (1.162)	(1,2)	$6 \cdot 10^{-7}$ ($3 \cdot 10^{-7}$)	0.26 (0.05)	-0.20 (0.05)	0.93 (0.02)	–
7 Investor	-0.0002 (0.0001)	0.751 (0.028)	0.125 (0.034)	0.021 (0.014)	0.043 (0.012)	0.011 (0.009)	0.010 (0.527)	(1,2)	$1 \cdot 10^{-7}$ ($6 \cdot 10^{-8}$)	0.36 (0.04)	-0.26 (0.04)	0.91 (0.01)	–
8 Legg Mason	$1 \cdot 10^{-4}$ ($7 \cdot 10^{-5}$)	0.829 (0.007)	0.021 (0.005)	0.022 (0.007)	0.011 (0.006)	0.034 (0.008)	0.142 (0.280)	(1,2)	$6 \cdot 10^{-8}$ ($2 \cdot 10^{-8}$)	0.15 (0.03)	-0.08 (0.03)	0.93 (0.01)	–
9 Millennium	-0.0002 ($6 \cdot 10^{-5}$)	0.820 (0.007)	0.009 (0.004)	0.039 (0.006)	0.027 (0.005)	0.014 (0.006)	0.132 (0.282)	(2,1)	$8 \cdot 10^{-8}$ ($4 \cdot 10^{-8}$)	0.13 (0.03)	–	0.40 (0.21)	0.47 (0.20)
10 Novo	-0.0001 (0.0001)	0.123 (0.034)	0.656 (0.022)	0.033 (0.010)	0.034 (0.009)	-0.004 (0.008)	0.235 (0.622)	(1,2)	$9 \cdot 10^{-8}$ ($4 \cdot 10^{-8}$)	0.41 (0.09)	-0.29 (0.09)	0.89 (0.02)	–
11 Pioneer	-0.0002 ($7 \cdot 10^{-5}$)	0.896 (0.006)	0.021 (0.005)	0.022 (0.006)	0.003 (0.004)	0.006 (0.006)	-0.210 (0.278)	(2,1)	$9 \cdot 10^{-8}$ ($4 \cdot 10^{-8}$)	0.13 (0.02)	–	0.41 (0.10)	0.45 (0.09)
12 PKO	$6 \cdot 10^{-5}$ (0.0001)	0.690 (0.032)	0.095 (0.022)	0.025 (0.014)	0.024 (0.011)	0.009 (0.007)	-0.337 (0.558)	(1,2)	$7 \cdot 10^{-8}$ ($6 \cdot 10^{-8}$)	0.27 (0.03)	-0.17 (0.03)	0.90 (0.01)	–
13 PZU	$-7 \cdot 10^{-5}$ ($6 \cdot 10^{-5}$)	0.841 (0.005)	0.010 (0.004)	-0.002 (0.005)	0.007 (0.004)	0.004 (0.005)	-0.206 (0.182)	(1,1)	$6 \cdot 10^{-8}$ ($2 \cdot 10^{-8}$)	0.10 (0.02)	–	0.90 (0.02)	–
14 Skarbiec	(0.0001)	0.330 (0.112)	0.491 (0.096)	0.025 (0.016)	0.037 (0.014)	0.024 (0.016)	0.633 (0.798)	(1,2)	$6 \cdot 10^{-7}$ ($6 \cdot 10^{-7}$)	0.24 (0.04)	-0.16 (0.04)	0.91 (0.02)	–
15 UmiKorona	$-8 \cdot 10^{-5}$ (0.0002)	0.393 (0.050)	0.545 (0.045)	0.032 (0.016)	0.042 (0.013)	0.024 (0.014)	0.908 (1.093)	(1,2)	$8 \cdot 10^{-7}$ ($5 \cdot 10^{-7}$)	0.28 (0.04)	-0.19 (0.04)	0.90 (0.03)	–

Notes: The table is based on the whole sample P1.

The T-M-FF-C (1) is the modified version of the Treynor-Mazuy model with the FF-spread variables (SMB and HML), the C-momentum variable (WML) and the lagged excess return on market portfolio M as additional factors.

The heteroskedastic consistent standard errors are in the parentheses below the coefficient estimates.

Source: Author's calculations (using *Gretl 1.9.5*).

Table 7. GARCH(p, q) versions of the H-M-FF-C market-timing models (2) of Polish equity mutual funds (from Jan 2, 2003 to Dec 31, 2010)

Equity fund	H-M-FF-C model (2) – conditional mean equation										Conditional variance equation					
	$\hat{\alpha}_p$	$\hat{\beta}_{1p}$	$\hat{\delta}_{1p}$	$\hat{\delta}_{2p}$	$\hat{\delta}_{3p}$	$\hat{\gamma}_p$	GARCH(p, q)	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\beta}_1$	$\hat{\beta}_2$				
1 Arka	0.0005 (0.0002)	0.779 (0.020)	0.059 (0.011)	0.024 (0.009)	0.017 (0.011)	-0.069 (0.034)	(1,1)	$2 \cdot 10^{-7}$ ($1 \cdot 10^{-7}$)	0.09 (0.02)	–	0.91 (0.02)	–				
2 Aviva	0.0006 (0.0002)	0.782 (0.028)	0.031 (0.007)	0.010 (0.006)	0.033 (0.006)	-0.140 (0.036)	(1,2)	$2 \cdot 10^{-7}$ ($7 \cdot 10^{-8}$)	0.51 (0.18)	-0.32 (0.17)	0.84 (0.03)	–				
3 BPH	$-8 \cdot 10^{-5}$ ($8 \cdot 10^{-5}$)	0.843 (0.009)	0.016 (0.004)	0.007 (0.004)	0.011 (0.005)	0.007 (0.013)	(1,2)	$6 \cdot 10^{-8}$ ($2 \cdot 10^{-8}$)	0.15 (0.03)	-0.07 (0.03)	0.92 (0.01)	–				
4 ING	-0.0001 ($8 \cdot 10^{-5}$)	0.900 (0.010)	0.016 (0.008)	0.003 (0.007)	0.010 (0.005)	0.003 (0.015)	(1,1)	$7 \cdot 10^{-8}$ ($2 \cdot 10^{-8}$)	0.08 (0.01)	–	0.91 (0.01)	–				
5 Investor 25	$-3 \cdot 10^{-5}$ (0.0002)	0.407 (0.030)	0.169 (0.022)	0.110 (0.019)	0.018 (0.013)	-0.003 (0.054)	(1,2)	$1 \cdot 10^{-6}$ ($8 \cdot 10^{-7}$)	0.27 (0.06)	-0.13 (0.08)	0.85 (0.06)	–				
6 Investor ADS	-0.0004 (0.0002)	0.572 (0.090)	0.001 (0.018)	0.058 (0.015)	0.010 (0.015)	0.049 (0.066)	(1,2)	$6 \cdot 10^{-7}$ ($3 \cdot 10^{-7}$)	0.26 (0.05)	-0.19 (0.05)	0.93 (0.02)	–				
7 Investor	-0.0002 (0.0001)	0.754 (0.032)	0.021 (0.014)	0.043 (0.012)	0.011 (0.009)	0.006 (0.034)	(1,2)	$1 \cdot 10^{-7}$ ($6 \cdot 10^{-8}$)	0.36 (0.04)	-0.26 (0.04)	0.91 (0.01)	–				
8 Legg Mason	$8 \cdot 10^{-5}$ ($9 \cdot 10^{-5}$)	0.833 (0.012)	0.022 (0.007)	0.011 (0.006)	0.033 (0.008)	0.008 (0.019)	(1,2)	$6 \cdot 10^{-8}$ ($2 \cdot 10^{-8}$)	0.15 (0.03)	-0.09 (0.03)	0.93 (0.01)	–				
9 Millennium	-0.0001 ($9 \cdot 10^{-5}$)	0.814 (0.010)	0.038 (0.006)	0.026 (0.005)	0.014 (0.006)	-0.009 (0.019)	(2,1)	$8 \cdot 10^{-8}$ ($4 \cdot 10^{-8}$)	0.13 (0.03)	–	0.40 (0.21)	0.47 (0.20)				
10 Novo	-0.0003 (0.0001)	0.146 (0.033)	0.034 (0.009)	0.035 (0.008)	-0.003 (0.008)	0.050 (0.031)	(1,2)	$9 \cdot 10^{-8}$ ($4 \cdot 10^{-8}$)	0.41 (0.09)	-0.28 (0.09)	0.89 (0.02)	–				
11 Pioneer	-0.0002 ($9 \cdot 10^{-5}$)	0.893 (0.011)	0.023 (0.005)	0.004 (0.004)	0.001 (0.006)	-0.008 (0.017)	(2,1)	$9 \cdot 10^{-8}$ ($4 \cdot 10^{-8}$)	0.13 (0.02)	–	0.42 (0.10)	0.45 (0.10)				
12 PKO	0.0001 (0.0001)	0.678 (0.039)	0.025 (0.014)	0.024 (0.012)	0.008 (0.007)	-0.027 (0.037)	(1,2)	$7 \cdot 10^{-8}$ ($6 \cdot 10^{-8}$)	0.27 (0.04)	-0.17 (0.04)	0.90 (0.02)	–				
13 PZU	$3 \cdot 10^{-5}$ ($8 \cdot 10^{-5}$)	0.828 (0.008)	-0.002 (0.004)	0.006 (0.004)	0.004 (0.005)	-0.027 (0.014)	(1,1)	$6 \cdot 10^{-8}$ ($3 \cdot 10^{-8}$)	0.10 (0.02)	–	0.90 (0.02)	–				
14 Skarbiec	-0.0002 (0.0002)	0.364 (0.114)	0.026 (0.016)	0.038 (0.014)	0.025 (0.016)	0.065 (0.051)	(1,2)	$6 \cdot 10^{-7}$ ($6 \cdot 10^{-7}$)	0.24 (0.03)	-0.16 (0.04)	0.91 (0.02)	–				
15 UmiKorona	-0.0003 (0.0002)	0.433 (0.052)	0.033 (0.016)	0.043 (0.013)	0.025 (0.014)	0.079 (0.056)	(1,2)	$8 \cdot 10^{-7}$ ($5 \cdot 10^{-7}$)	0.28 (0.04)	-0.19 (0.04)	0.90 (0.03)	–				

Notes: The table is based on the whole sample P1.

The H-M-FF-C (2) is the modified version of the Henriksson-Merton model with the FF-spread variables (SMB and HML), the C-momentum variable (WML) and the lagged excess return on market portfolio M as additional factors.

The heteroskedastic consistent standard errors are in the parentheses below the coefficient estimates.

Source: Author's calculations (using *Gretl 1.9.5*).

the momentum factor (WML) influence is not statistically significant (cf. the $\hat{\delta}_{3p}$ estimates). Therefore, our results suggest that the momentum factor has little explanatory power for our sample of funds.

With respect to the estimates of market-timing skills ($\hat{\gamma}_p$), we observe that they are statistically significant only in the case of two out of fifteen funds (Table 6) and three out of fifteen funds (Table 7). Therefore, the null hypothesis (4) is rejected only in these cases. These empirical results show no statistical evidence that Polish equity fund managers have outguessed the market in the period from Jan 2, 2003 to Dec 31, 2010⁴⁶.

Conclusions

This paper examines GARCH(p, q) versions of the modified T-M-FF-C and H-M-FF-C market-timing models of Polish equity open-end mutual funds, with Fama & French's spread variables, Carhart's momentum factor and lagged values of the market factor as an additional independent variables. We include lagged values of the market factor as an additional variable in the regressions of the models because of the pronounced "Fisher effect" in the case of the main Warsaw Stock Exchange indexes. We detect for the ARCH(q) effects in market-timing models in the period investigated January 2, 2003 – December 31, 2010. Our empirical results can be summarized as follows.

- 1) The research provide evidence of strong ARCH effects⁴⁷ in the market-timing models of Polish equity open-end mutual funds.
- 2) For the reason of the existence of the strong ARCH effects in the market-timing models, the GARCH(p, q) versions of these models seem to be appropriate for estimation in the case of the group of mutual funds from the same risk class.
- 3) There is no evidence that equity funds' managers are successful in selectivity.
- 4) The levels of systematic risks are significantly positive.
- 5) The regressions including lagged values of the market factor as an additional independent variable are well-founded.
- 6) As for the influence of the size (SMB), book-to-market (HML) and momentum (WML) factors, it is different, but not controversial. The evidence is that the size factor influence is comparable to the book-to-market factor influence.
- 7) The momentum factor (WML) influence is not statistically significant.
- 8) The empirical results show no statistical evidence that Polish equity fund managers have outguessed the market in the period from Jan 2, 2003 to Dec 31, 2010. Probably

the point is that mutual fund performance is affected by its operating style and purpose. If the purpose of the fund is to follow the market, its performance will be close to the market and should show no superior performance. Therefore, it may be preferable to also include the operating style and purpose of the funds as another factor⁴⁸.

As for the practical implications of the results it is worthwhile to note that the influence of the size (SMB), book-to-market (HML) and momentum (WML) factors is different in various sub-samples⁴⁹. It is worth stressing that SMB, HML, and WML factors have a diverse explanatory power for the sample of funds. Another important finding is that the investigated funds are not homogeneous regarding the influence of the size, book-to-market and momentum factors, despite the fact that all of them are Polish equity open-end mutual funds.

A possible direction for further investigation would be the performance evaluation in terms of modified market-timing models as the FACTOR-ARCH models⁵⁰.

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Notes

¹ Treynor, Mazuy (1966).

² Henriksson, Merton (1981).

³ Merton (1981).

⁴ For example, Ferson, Schadt (1996), Bollen, Busse (2001), Prather, Middleton (2006), Romacho, Cortez (2006), Olbryś (2010a), Olbryś (2010b).

⁵ For example, Henriksson (1984); Henriksson, Merton (1981).

⁶ Carhart (1997).

⁷ Kao et al. (1998).

⁸ Olbryś (2010a, 2011a), Zellner (1962).

⁹ Engle (1982).

¹⁰ Tsay (2010), p. 231.

¹¹ Campbell et al. (1997), p. 83.

¹² For example, Fama (1970), Fisher (1966), Dimson (1979), Scholes, Williams (1977), Perry (1985), Roll (1981), Schwartz, Whitcomb (1977), Shanken (1987), Rosenberg, Rudd (1982).

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- ¹³ Scholes, Williams (1977).
- ¹⁴ Cohen et al. (1980).
- ¹⁵ Atchison et al. (1987).
- ¹⁶ Campbell et al. (1997), p. 84.
- ¹⁷ Busse (1999), Dimson (1979).
- ¹⁸ Olbryś (2010b), Fama, French's (1993).
- ¹⁹ Rouwenhorst (1998).
- ²⁰ Carhart (1997), Olbryś (2011b).
- ²¹ Olbryś (2011a).
- ²² Jensen (1968).
- ²³ Olbryś (2011a).
- ²⁴ Jensen (1968).
- ²⁵ Henriksson (1984).
- ²⁶ Engle (1982), pp. 988–989.
- ²⁷ Engle (1982), Bollerslev (1986).
- ²⁸ Adkins (2010), p. 196.
- ²⁹ Bollerslev (1986), p. 309.
- ³⁰ See for example Engle (2000).
- ³¹ See Bollerslev, Wooldridge (1992).
- ³² Tsay (2010), p. 120.
- ³³ Greene (2002), p. 244.
- ³⁴ Ljung, Box (1978).
- ³⁵ Tsay (2010), p. 33.
- ³⁶ Engle (1982).
- ³⁷ Lee (1991), pp. 269–270.
- ³⁸ Greene (2002), p. 244.
- ³⁹ Dimson (1979), Busse (1999), Olbryś (2011a).
- ⁴⁰ Tsay (2010).
- ⁴¹ Ibidem, pp. 133–134.
- ⁴² Bollerslev, Wooldridge (1992).
- ⁴³ Cf. Engle (2000), p. 387, Fiszeder (2009), pp. 26–28.
- ⁴⁴ Bollerslev, Wooldridge (1992).
- ⁴⁵ Tsay (2010), p. 483.
- ⁴⁶ This evidence is consistent with most of the literature on mutual fund performance, for example: Treynor, Mazuy (1966), Henriksson (1984), Bollen, Busse (2001), Prather, Middleton (2006), Romacho, Cortez (2006).
- ⁴⁷ Engle (1982).
- ⁴⁸ Cf. Wermers (2000).
- ⁴⁹ Olbryś (2011c).
- ⁵⁰ Cf. Engle (2000), pp. 277–299.

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