DYNAMIC ECONOMETRIC MODELS
Vol. 11 – Nicolaus Copernicus University – Toruń – 2011

Joanna Olbryś
Bialystok University of Technology

ARCH Effect in Classical Market-Timing Models with Lagged Market Variable: the Case of Polish Market[†]

A b s t r a c t. The main goal of this study is to present the regressions of the GARCH versions of classical market-timing models of Polish equity funds. We examine the models with lagged values of the market factor as an additional variable because of the Fisher's effect[1] in the case of the main Warsaw Stock Exchange indexes. The market-timing and selectivity abilities of fund managers are evaluated for the period Jan 2003 – June 2011. Results on both the HAC and the GARCH estimates are qualitatively similar, and even better in the case of the simpler HAC method. For this reason, it is not necessary to estimate the GARCH versions of market-timing models in the case of Polish mutual funds, even despite the strong ARCH effects that exist in these models.

K e y w o r d s: market-timing, non-trading, ARCH effect, GARCH model.

Introduction

Market-timing is one strategy by which portfolio managers might attempt to obtain returns in excess of those expected of an unmanaged portfolio. One of the benefits of market-timing is the production of a positively skewed distribution of returns. Treynor and Mazuy (1966) produce a single factor model derived from CAPM in which a quadratic term is added to reflect the market-timing. The T-M coefficient measures the co-skewness with the benchmark portfolio. Henriksson and Merton (1981) start from a similar idea, but provide a different interpretation of market-timing ability. Adding a term in the CAPM model that contains a dummy variable based on the difference between market return and the risk-free rate, they permit managers to choose between two levels of market risk: an up-market and a down-market beta (Cogneau, Hübner, 2009). Some other researchers extend market-timing models to multifactor as well as

---

[†] The author acknowledges the financial support in 2009 – 2011 from the Polish Ministry of Science and Higher Education within the grant no. N N113 173237.

[1] Lawrence Fisher's effect (1966)

to conditional versions. In relation to the Polish market, in Olbryś (2009) the usefulness of the conditional multifactor market-timing models for the investment managers' performance evaluation on the Polish market has been examined. Ferson and Schadt (1996) use a collection of public information variables. In Poland, the suitable variables are: (1) the lagged monthly dividend yield of the WSE stock index, (2) the lagged monthly level of the 1M WIBOR, (3) the lagged monthly measure of the slope of the term structure (Olbryś, 2009, p. 522). The evidence on Polish market shows that the quality and usefulness of these models is rather low. As for the other multifactor models, in light of the empirical results for the Polish market, the influence of the Fama and French's (1993) size (SMB) and book-to-market (HML) spread variables, and Carhart's (1997) momentum (WML) factor on the Polish equity funds' market seems to be rather controversial (Olbryś, 2010a b; 2012). It is worth stressing that the SMB, HML, and WML factors have a diverse explanatory power for the sample of Polish 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 (Olbryś, 2011a). For this reason, the SMB, HML, and WML factors have not been taken into account as explanatory variables in our models.

According to the literature, the methods most widely applied in market-timing models estimation are the two proposed by White (1980) or Newey-West (1987) (see e.g. Ferson, Schadt, 1996; Bollen, Busse, 2001; Romacho, Cortez, 2006; Olbryś, 2010a, b). Some previous publications also describe applications of the GLS procedure with correction for heteroskedasticity (see e.g. Henriksson, Merton, 1981; Henriksson, 1984) or the Fama-MacBeth cross-sectional regression approach from 1973 (Carhart, 1997). Kao et al. (1998) employ an autoregressive conditional heteroskedastic (ARCH) model, but without testing the ARCH effects. Recent studies in multifactor market-timing models in the case of Polish equity funds by Olbryś (2010a) present possibilities and examples of applying the seemingly unrelated regression method (SUR) which was described by Zellner (1962). The author's recent research provide evidence of pronounced ARCH effects (Engle, 1982) in the market-timing models of Polish equity open-end mutual funds. For this reason, the main goal of this study is to present the regression results of the new GARCH(p, q) models of these funds. We estimate the GARCH versions of classical market-timing models with lagged values of the market factor as an additional independent variable because of the pronounced Fisher's 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 – June 2011. In comparison to robust Newey-West method results, our findings suggest that the GARCH(p, q) model is suitable but not necessary for such applications. To the best of author's knowledge, no such investigation has been undertaken for the Polish market.

The remainder of the paper is organized as follows. Section 1 specifies a methodological background and a brief literature review. First, we stress the validity of the non-trading problem and the Fisher's effect in the case of market-index returns. Next, we present classical market-timing models with lagged values of the market factor as additional explanatory variable. We also present a brief theoretical framework 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 emerging market and discuss the results obtained. Section 3 recalls the main findings and presents the conclusions.

1. Methodological Background

1.1. Non-trading Problem and the Fisher's Effect

It is worth stressing, that the empirical market microstructure literature is an extensive one recently. High-frequency financial data are important in studying a variety of issues related to the trading process and market microstructure (Tsay, 2010, p. 231). For some purposes, such aspects of the market microstructure as non-trading or bid-ask spread effects can be safely ignored. However, for other purposes, market microstructure is central (Campbell et al., 1997). 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 process (see e.g. Fisher, 1966; Scholes and Williams, 1977; Dimson, 1979), also on the Polish capital market (see e.g. Doman, Doman, 2004; Doman, 2010; Brzeszczyński et al., 2011; Olbryś, 2011b). It is worthwhile to note that two common elements among most of the phenomena are evident, the "interval effect" and the impact of a security's "thinness". The evidence that daily market-index returns exhibit a pronounced positive first-order autocorrelation has been called the Fisher's effect since Lawrence Fisher in 1966 hypothesized its probable cause. Fisher suggested it was caused by a non-trading of the component securities. The observed correlation is higher in those indexes that give greater weight to the securities of smaller firms. To detect for the Fisher's effect in the market-index returns, partial autocorrelations functions (PACF) can be calculated. To calculate PACF, first it should be determined (based on the ADF test) that the analyzed index series are stationary. In the next step partial autocorrelations functions for individual stationary processes can be calculated and the significance of the first-order daily serial correlation coefficients ρ_1 can be tested, using the Quenouille's test (Kufel, 2009). The evaluation of first-order serial correlation is carried out by testing the null hypothesis:

$$H_0 : \rho_1 = 0 \tag{1}$$

If the estimate $\hat{\rho}_1$ satisfies the inequality $|\hat{\rho}_1| \leq \frac{1.96}{\sqrt{T}}$, then we have no reason to reject the null hypothesis (1).

The non-trading 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 coefficients (Campbell et al., 1997, p. 84). For this reason, Busse (1999) proposed lagged values of the market factor as an additional independent variable in the regressions of market-timing models using Dimson's (1979) correction. We emphasize that the Polish market is an emerging market and it can be expected that non-trading problem should be more visible than in other, developed markets.

1.2. Classical Market-Timing Models with Lagged Market Variable

The classical parametric Treynor – Mazuy market-timing model with lagged values of the market factor as additional explanatory variable can be expressed as:

$$r_{P,t} = \alpha_P + \beta_{1P} \cdot r_{M,t} + \beta_{2P} \cdot r_{M,t-1} + \gamma_P \cdot (r_{M,t})^2 + \varepsilon_{P,t}, \tag{2}$$

where $R_{F,t}$ 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*, α_P measures the selectivity skills of the manager (Jensen, 1968), 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, γ_P measures the market-timing skills of the manager of portfolio *P* (the T-M coefficient), and $\varepsilon_{P,t}$ 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 (2), the classical parametric Henriksson - Merton model with lagged values of the market factor as additional explanatory variable can be expressed as:

$$r_{P,t} = \alpha_P + \beta_{1P} \cdot r_{M,t} + \beta_{2P} \cdot r_{M,t-1} + \gamma_P \cdot y_{M,t} + \varepsilon_{P,t}, \tag{3}$$

where $r_{P,t}$, $r_{M,t}$, $r_{M,t-1}$, α_P, β_{1P}, β_{2P}, $\varepsilon_{P,t}$ are as in equation (2), γ_P measures the market-timing skills of the manager of portfolio *P* (the H-M coefficient), 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 (2)–(3) will be positive (Jensen, 1968). 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:

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

i.e., the manager does not have any microforecasting ability. The evaluation of market-timing skills is carried out by testing the null hypothesis:

$$H_0 : \gamma_P = 0 \tag{5}$$

i.e., the manager does not possess any timing ability or does not on his forecast (Henriksson 1984). A negative value for the regression estimate $\hat{\gamma}_P$ would imply a negative value for market-timing. The size of the estimate $\hat{\gamma}_P$ informs us about the manager's market skills.

1.3. The GARCH(p, q) Model

The first model that provides a systematic framework for volatility modeling is the ARCH model of Engle (1982). Engle proposed the ARCH models to capture the serial correlation of volatility (Campbell et al., 1997, p. 482). Engle suggested the ARCH model as an alternative to the usual time-series process. More recent studies of financial markets suggest that the phenomenon is quite common (Greene, 2002). The basic idea of the ARCH models is that 1) the innovation ε_t of the regression is serially uncorrelated, but dependent, and 2) the dependence of ε_t can be described by a simple quadratic function of its lagged values (Tsay, 2010). 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 $x_t\mathbf{b}$, a linear combination of lagged endogenous and exogenous variables included in the information set ψ_{t-1}, with $\mathbf{b}$ a vector of unknown parameters (Engle, 1982). Formally:

$$\begin{aligned} & y_t | \psi_{t-1} \sim N(x_t\mathbf{b}, h_t), \\ & \varepsilon_t = y_t - x_t\mathbf{b}, \\ & h_t = h(\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-q}, \boldsymbol{\alpha}) = \alpha_0 + \sum_{i=1}^{q} \alpha_i \cdot \varepsilon_{t-i}^2, \\ & \alpha_0 > 0, \alpha_i \geq 0, i = 1, \ldots, q. \end{aligned} \tag{6}$$

where ε_t is the innovation in a linear regression with $V(\varepsilon) = \sigma^2$, q is the order of the ARCH(q) process, $\boldsymbol{\alpha}$ is the vector of unknown parameters, h_t is the variance function.
The null hypothesis of white noise disturbances in (6) is:

$$H_0 : \alpha_1 = \cdots = \alpha_q = 0 \quad (7)$$

The GARCH(p, q) model generalizes the ARCH(q) model of Engle (1982) and is proposed by Bollerslev (1986). The GARCH(p, q) is given by:

$$\begin{aligned} & y_t \left| \psi_{t-1} \sim N(x_t \mathbf{b}, h_t), \right. \\ & \varepsilon_t = y_t - x_t \mathbf{b}, \\ & h_t = h(\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-q}, h_{t-1}, h_{t-2}, \ldots, h_{t-p}, \boldsymbol{\alpha}, \boldsymbol{\beta}) = \\ & = \alpha_0 + \sum_{i=1}^{q} \alpha_i \cdot \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \cdot h_{t-j}, \\ & \alpha_0 > 0,\ \alpha_i \geq 0, i = 1, \ldots, q, q > 0,\ \beta_j \geq 0, j = 1, \ldots, p, p \geq 0. \end{aligned} \quad (8)$$

where ε_t, q, $\boldsymbol{\alpha}$, h_t are as in equation (6) and $\boldsymbol{\beta}$ 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 variance (Adkins, 2010). 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 (8) is:

$$H_0 : \alpha_1 = \cdots = \alpha_q = 0; \beta_1 = \cdots = \beta_p = 0 \quad (9)$$

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 the lagged conditional variances to enter as well (Bollerslev 1986). A wide range of GARCH models have now appeared in the econometric literature (e.g. Engle, 2000; Fiszeder, 2009). The parameters of GARCH(p, q) models are almost invariably estimated via Maximum Likelihood (ML) or Quasi-Maximum Likelihood (QML: see Bollerslev, Wooldridge, 1992) 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 (Tsay, 2010).

1.4. Testing for ARCH Effect in an Econometric Model

Before estimating the GARCH(p, q) model it might be useful to test for the ARCH effect. 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 effects (Greene, 2002). Two tests are available. The first test is to apply the Ljung-Box statistics $Q(q)$ (Ljung, Box, 1978). 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 performance (Tsay, 2010, p. 33). The second test for conditional heteroskedasticity is the Lagrange multiplier (LM) test of Engle (1982). Lee (1991) 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. This implies that under the null hypothesis of white noise, the GARCH(p, q) effect and the ARCH(q) effect are locally equivalent alternatives. Hence we can proceed by testing the ARCH(q) effect against the GARCH(p, q) effect (Lee, 1991, pp. 269–270).

An LM test of ARCH(q) against the hypothesis of no ARCH effects can be carried out by computing $\chi_q^2 = T \cdot R^2$ in the regression of e_t^2 on a constant and q lagged values. Under the null hypothesis of no ARCH effects, 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) effects (Greene, 2002, p. 244).

2. Empirical Results

2.1. The Fisher's Effect on the Warsaw Stock Exchange

The Fisher's effect on the Warsaw Stock Exchange has been detected by Olbryś (2011b). The empirical results show a pronounced Fisher's 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 (1) only in the case of the WIG20 series. As mentioned above, this evidence is consistent with most of the literature on friction in the trading process because the observed correlation is higher in those indexes that give greater weight to the securities of smaller firms. For the Fisher's effect reason, we can use Dimson's (1979) 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 trading (Olbryś, 2011a).

2.2. Data

The period investigated is January 2, 2003 – June 30, 2011 (T=2137 observations). To detect for the ARCH effect in market-timing models of Polish funds in subsamples of various length, the entire sample has been divided into eight subsamples: P1, P2, P3, P4, P5, P6, P7, P8 (Table 1).

Table 1. Subsamples in the period from Jan 2, 2003 to June 30, 2011

Subsample		T
P1	Jan 2, 2003–June 30, 2011	2137
P2	Jan 2, 2004–June 30, 2011	1886
P3	Jan 3, 2005–June 30, 2011	1631
P4	Jan 2, 2006–June 30, 2011	1380
P5	Jan 2, 2007–June 30, 2011	1129
P6	Jan 2, 2008–June 30, 2011	880
P7	Jan 5, 2009–June 30, 2011	629
P8	Jan 4, 2010–June 30, 2011	377

Note: T is the number of data points.

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

	Equity fund (current name)	Short Name	Year of creation
1	Arka BZ WBK FIO Subfundusz Arka Akcji	Arka	1998
2	Aviva Investors FIO Subfundusz Aviva Investors Polskich Akcji	Aviva	2002
3	BPH FIO Parasolowy BPH Subfundusz Akcji	BPH	1999
4	ING Parasol FIO ING Subfundusz Akcji	ING	1998
5	Investor Top 25 Małych Spółek FIO	Investor 25	2002
6	Investor Akcji Dużych Spółek FIO	Investor ADS	1998
7	Investor Akcji FIO	Investor	1998
8	Legg Mason Akcji FIO	Legg Mason	1999
9	Millennium FIO Subfundusz Akcji	Millennium	2002
10	Novo FIO Subfundusz Novo Akcji	Novo	1998
11	Pioneer FIO Subfundusz Pioneer Akcji Polskich	Pioneer	1995
12	PKO Akcji – FIO	PKO	1998
13	PZU FIO Parasolowy Subfundusz PZU Akcji Krakowiak	PZU	1999
14	Skarbiec FIO Subfundusz Akcji Skarbiec – Akcji	Skarbiec	1998
15	UniFundusze FIO Subfundusz UniKorona Akcje	UniKorona	1997

Note: The source of this Table is the Polish Financial Supervision Authority http://www.knf.gov.pl (Sept 8, 2011).

We have examined the performance of 15 selected equity open-end 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 2011, therefore our results are free of survivorship bias (Table 2). We have studied daily logarithmic excess returns from Jan 2003 to June 2011. Daily returns on the main index of WSE 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. All calculations were done using *Gretl 1.9.5.*

2.3. ARCH Effect in Market-Timing Models with Lagged Market Variable

Volatility clustering, which is a common cause of heteroskedasticity, is more likely to be present in financial models built using higher-frequency data, such as daily data (Brzeszczyński et al., 2011). To detect for the ARCH effect in market-timing models of Polish equity open-end mutual fund portfolios in the period investigated Jan 2, 2003 – June 30, 2011, the LM (Lagrange Multiplier) and the LB (Ljung-Box) tests have been applied. The empirical results presented in Table 3 show strong ARCH effect in the case of all of the funds. The null hypothesis (7) is rejected in these cases. Because we are using daily logarithmic excess returns on fund portfolios, the LM test at the lag $q = 5$ has been applied. On the other hand, the LB test at the lag $q \approx \ln(2137) \approx 8$ has been used (Tsay, 2010). The p-values of all statistics are very close to zero.

Table 3. The ARCH effect in market-timing models (2) and (3) of Polish equity mutual funds in the entire sample P1 (period from Jan 2, 2003 to June 30, 2011)

	Equity fund	T-M model				H-M model			
	(short name)	LM	p-value	LB	p-value	LM	p-value	LB	p-value
1	Arka	326.8	$1 \cdot 10^{-68}$	157.6	$4 \cdot 10^{-30}$	346.9	$7 \cdot 10^{-73}$	159.5	$2 \cdot 10^{-30}$
2	Aviva	257.1	$1 \cdot 10^{-53}$	299.9	$4 \cdot 10^{-60}$	258.3	$9 \cdot 10^{-54}$	306.7	$1 \cdot 10^{-61}$
3	BPH	424.6	$1 \cdot 10^{-89}$	434.2	$9 \cdot 10^{-89}$	427.0	$4 \cdot 10^{-90}$	436.5	$2 \cdot 10^{-89}$
4	ING	443.9	$1 \cdot 10^{-93}$	442.4	$1 \cdot 10^{-90}$	445.2	$5 \cdot 10^{-94}$	444.5	$5 \cdot 10^{-91}$
5	Investor 25	404.4	$3 \cdot 10^{-85}$	145.1	$2 \cdot 10^{-27}$	390.4	$3 \cdot 10^{-82}$	142.1	$8 \cdot 10^{-27}$
6	Investor ADS	524.4	$4 \cdot 10^{-111}$	474.7	$1 \cdot 10^{-97}$	531.8	$1 \cdot 10^{-112}$	475.1	$1 \cdot 10^{-97}$
7	Investor	460.3	$2 \cdot 10^{-97}$	498.0	$1 \cdot 10^{-102}$	459.4	$4 \cdot 10^{-97}$	497.2	$2 \cdot 10^{-102}$
8	Legg Mason	402.1	$1 \cdot 10^{-84}$	333.1	$3 \cdot 10^{-67}$	408.6	$4 \cdot 10^{-86}$	334.2	$2 \cdot 10^{-67}$
9	Millennium	437.6	$2 \cdot 10^{-92}$	371.2	$2 \cdot 10^{-75}$	439.8	$7 \cdot 10^{-93}$	374.7	$4 \cdot 10^{-76}$
10	Novo	622.2	$3 \cdot 10^{-132}$	489.3	$1 \cdot 10^{-100}$	609.5	$1 \cdot 10^{-129}$	485.7	$8 \cdot 10^{-100}$
11	Pioneer	423.7	$2 \cdot 10^{-89}$	372.1	$1 \cdot 10^{-75}$	426.6	$5 \cdot 10^{-90}$	374.4	$5 \cdot 10^{-76}$
12	PKO	485.9	$8 \cdot 10^{-103}$	379.1	$5 \cdot 10^{-77}$	477.1	$7 \cdot 10^{-101}$	379.0	$5 \cdot 10^{-77}$
13	PZU	402.0	$1 \cdot 10^{-84}$	387.0	$1 \cdot 10^{-78}$	404.9	$2 \cdot 10^{-85}$	391.8	$1 \cdot 10^{-79}$
14	Skarbiec	384.4	$6 \cdot 10^{-81}$	427.0	$3 \cdot 10^{-87}$	385.5	$4 \cdot 10^{-81}$	426.7	$3 \cdot 10^{-87}$
15	UniKorona	371.4	$4 \cdot 10^{-78}$	519.3	$5 \cdot 10^{-107}$	376.8	$2 \cdot 10^{-79}$	519.7	$4 \cdot 10^{-107}$

Note: The table is based on the entire sample P1; T-M (2) is the classical Treynor-Mazuy model with the lagged excess return on market portfolio M as additional factor; H-M (3) is the classical Henriksson-Merton model with the lagged excess return on market portfolio M as additional factor; LM is the Engle (1982) statistic at the lag equal to five, which should be distributed as chi-squared; LB is the Ljung-Box (1978) statistic at the lag equal to eight, which should be distributed as chi-squared.

Tables 4a–4b present further analysis, including more details about empirical results of testing the ARCH effect in the T-M and the H-M market-timing models. The ARCH effect has been tested in the case of all funds and in all subsamples.

Several results in Tables 4a–4b are worth special notice. The ARCH effect disappears as the interval is shortened and only in the case of 5 out of 15 funds (i.e. Arka, Investor 25, Novo, Skarbiec and UniKorona) it persists in all samples P1–P8. Furthermore, if the ARCH effects are not present in the model, simple OLS regression is quite sufficient (Brzeszczyński et al., 2011).

Table 4a. Result summary of the ARCH effect in the T-M and H-M models; subsamples P1–P4

Fund. No.	P1				P2				P3				P4			
	T-M		H-M		T-M		H-M		T-M		H-M		T-M		H-M	
	LM	LB	LM	LB	LM	LB	LM	LB	LM	LB	LM	LB	LM	LB	LM	LB
1	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
2	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
3	+	+	+	+	+	+	+	+	+	-	+	-	+	-	+	-
4	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
5	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
6	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
7	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
8	+	+	+	+	+	+	+	+	+	-	+	-	+	-	+	-
9	+	+	+	+	+	+	+	+	+	-	+	-	+	-	+	-
10	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
11	+	+	+	+	+	+	+	+	+	-	+	-	+	-	+	-
12	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
13	+	+	+	+	+	+	+	+	+	-	+	-	+	-	+	-
14	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
15	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+

Table 4b. Result summary of the ARCH effect in the T-M and H-M models; subsamples P5–P8

Fund. No.	P5				P6				P7				P8			
	T-M		H-M		T-M		H-M		T-M		H-M		T-M		H-M	
	LM	LB	LM	LB	LM	LB	LM	LB	LM	LB	LM	LB	LM	LB	LM	LB
1	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
2	+	+	+	+	-	+	-	+	-	+	-	+	+	+	+	+
3	+	-	+	-	+	-	+	-	-	-	-	-	+	-	+	-
4	+	+	+	+	+	-	+	-	+	-	+	-	-	+	-	+
5	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
6	+	+	+	+	+	+	+	+	+	+	+	+	-	-	-	-
7	+	+	+	+	+	+	+	+	+	+	+	+	+	-	+	-
8	+	-	+	-	+	-	+	-	+	+	+	+	-	-	-	-
9	+	-	+	-	+	-	+	-	+	-	+	-	+	-	+	-
10	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
11	+	-	+	-	+	-	+	-	+	-	+	-	-	-	-	-
12	+	+	+	+	+	+	+	+	+	-	+	-	-	-	-	-
13	+	-	+	-	+	-	+	-	+	+	+	+	+	+	+	+
14	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
15	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+

Note: Table 4a is based on the samples P1– P4 and Table 4b is based on the samples P5– P8 (Table 1); T-M (2) is the classical Treynor-Mazuy model with the lagged excess return on market portfolio M as additional factor; H-M (3) is the classical Henriksson-Merton model with the lagged excess return on market portfolio M as additional factor; LM is the Engle (1982) statistic at the lag q, which should be distributed as chi-squared; LB is the Ljung-Box (1978) statistic at the lag q, which should be distributed as chi-squared; + denotes that statistic value is larger than the critical table value of chi-squared and gives evidence of the presence of ARCH effect; – denotes that statistic value is smaller than the critical table value of chi-squared.

2.4. The GARCH Versions of Market-Timing Models of Polish Equity Mutual Funds

Hamilton (2008) stresses that even if the researcher's primary interest is in estimating the conditional mean, having a correct description of the conditional variance can still be quite important. By incorporating the observed features of the heteroskedasticity into the estimation of the conditional mean, substantially more efficient estimates of the conditional mean can be obtained. The most popular White or Newey–West corrections may not fully correct for the influence problems introduced by ARCH. The testing results from the Polish equity

Table 5a. The HAC estimates of the T-M market-timing models of Polish equity mutual funds in the entire period from Jan 2, 2003 to June 30, 2011

	Equity fund	$\hat{\alpha}_P$	$\hat{\beta}_{1P}$	β_{2P}	$\hat{\gamma}_P$	$\overline{R^2}$
1	Arka	$4\cdot10^{-4}$ ** $(1\cdot10^{-4})$	0.71*** (0.03)	0.14*** (0.03)	-1.86** (0.83)	0.66
2	Aviva	$3\cdot10^{-4}$ ** $(1\cdot10^{-4})$	0.75*** (0.03)	0.15*** (0.02)	-1.45** (0.69)	0.73
3	BPH	$2\cdot10^{-5}$ $(1\cdot10^{-4})$	0.72*** (0.02)	0.12*** (0.02)	-0.56 (0.48)	0.76
4	ING	$-2\cdot10^{-6}$ $(1\cdot10^{-4})$	0.76*** (0.02)	0.13*** (0.02)	-0.48 (0.43)	0.74
5	Investor 25	$2\cdot10^{-4}$ $(2\cdot10^{-4})$	0.39*** (0.02)	0.31*** (0.03)	-1.76** (0.85)	0.39
6	Investor ADS	$-1\cdot10^{-4}$ $(2\cdot10^{-4})$	0.63*** (0.03)	0.38*** (0.03)	-0.55 (1.26)	0.55
7	Investor	$-4\cdot10^{-5}$ $(1\cdot10^{-4})$	0.54*** (0.03)	0.37*** (0.03)	-0.75 (0.86)	0.55
8	Legg Mason	$2\cdot10^{-4}$ * $(9\cdot10^{-5})$	0.69*** (0.02)	0.12*** (0.02)	-0.68 (0.51)	0.74
9	Millennium	$-4\cdot10^{-6}$ $(1\cdot10^{-4})$	0.69*** (0.02)	0.13*** (0.02)	-0.76 (0.57)	0.72
10	Novo	$8\cdot10^{-5}$ $(2\cdot10^{-4})$	0.48*** (0.03)	0.45*** (0.02)	-1.20 (1.14)	0.55
11	Pioneer	$-9\cdot10^{-5}$ $(1\cdot10^{-4})$	0.80*** (0.03)	0.16*** (0.02)	-1.13 (0.81)	0.74
12	PKO	$6\cdot10^{-5}$ $(2\cdot10^{-4})$	0.55*** (0.03)	0.28*** (0.03)	-1.66 (1.19)	0.56
13	PZU	$3\cdot10^{-5}$ $(1\cdot10^{-4})$	0.71*** (0.02)	0.12*** (0.02)	-0.98** (0.49)	0.73
14	Skarbiec	$-4\cdot10^{-6}$ $(1\cdot10^{-4})$	0.46*** (0.03)	0.38*** (0.03)	0.15 (0.73)	0.51
15	UniKorona	$1\cdot10^{-4}$ $(1\cdot10^{-4})$	0.48*** (0.03)	0.45***(0.03)	-0.54 (0.89)	0.55

Note: The table is based on the entire sample P1; T-M (2) is the classical Treynor-Mazuy model with the lagged excess return on market portfolio M as additional factor; the heteroskedastic consistent standard errors are in parentheses next to the coefficient estimates; the values of the adjusted determination coefficient are in the last column; * significant at the 10 per cent level; ** significant at the 5 per cent level; *** significant at the 1 per cent level.

mutual funds dataset show pronounced ARCH effect in market-timing models (Tables 3–4). For this reason, the estimation of the market-timing models as the GARCH(p, q) models is well-founded. Although the ARCH(q) model (6) 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 (8). However, specifying the order of a GARCH(p, q) model is not easy. Only the lower order GARCH models are used in most applications, i.e. GARCH(1,1), GARCH(1,2), GARCH(2,1), and GARCH(2,2) models (Tsay, 2010). 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[2].

As an example, we present the comparison of the estimation results of market-timing models T-M and H-M of Polish equity mutual funds in the entire period from Jan 2, 2003 to June 30, 2011. We use the Newey-West robust estimates (HAC) as well as the robust quasi-maximum likelihood estimates (QML) of the parameters of the suitable GARCH(p, q) version of the market-timing model. Tables 5a–5b provide details on the robust HAC estimates of the T-M and H-M market-timing models, respectively.

Table 5b. The HAC estimates of the H-M market-timing models of Polish equity mutual funds in the entire period from Jan 2, 2003 to June 30, 2011

	Equity fund	$\hat{\alpha}_P$	$\hat{\beta}_{1P}$	β_{2P}	$\hat{\gamma}_P$	$\overline{R^2}$
1	Arka	$7 \cdot 10^{-4}$ ***($2 \cdot 10^{-4}$)	0.65*** (0.04)	0.14*** (0.03)	-0.14** (0.06)	0.66
2	Aviva	$6 \cdot 10^{-4}$ **($2 \cdot 10^{-4}$)	0.70*** (0.04)	0.15*** (0.02)	-0.11** (0.05)	0.73
3	BPH	$1 \cdot 10^{-4}$ ($1 \cdot 10^{-4}$)	0.70*** (0.03)	0.12*** (0.02)	-0.04 (0.04)	0.76
4	ING	$1 \cdot 10^{-4}$ ($1 \cdot 10^{-4}$)	0.74*** (0.03)	0.13*** (0.02)	-0.04 (0.04)	0.74
5	Investor 25	$4 \cdot 10^{-4}$ ($3 \cdot 10^{-4}$)	0.33*** (0.03)	0.31*** (0.03)	-0.13* (0.06)	0.39
6	Investor ADS	$-2 \cdot 10^{-4}$ ($3 \cdot 10^{-4}$)	0.63*** (0.04)	0.38*** (0.03)	-0.01 (0.08)	0.55
7	Investor	$2 \cdot 10^{-5}$ ($3 \cdot 10^{-4}$)	0.52***(0.03)	0.37*** (0.03)	-0.04 (0.06)	0.55
8	Legg Mason	$3 \cdot 10^{-4}$ *($1 \cdot 10^{-4}$)	0.67***(0.03)	0.12*** (0.02)	-0.05 (0.04)	0.74
9	Millennium	$2 \cdot 10^{-4}$ ($2 \cdot 10^{-4}$)	0.65*** (0.03)	0.13*** (0.02)	-0.07 (0.04)	0.72
10	Novo	$1 \cdot 10^{-4}$ ($3 \cdot 10^{-4}$)	0.45*** (0.03)	0.45*** (0.03)	-0.06 (0.07)	0.55
11	Pioneer	$9 \cdot 10^{-5}$ ($2 \cdot 10^{-4}$)	0.76*** (0.04)	0.16*** (0.02)	-0.08 (0.06)	0.74
12	PKO	$3 \cdot 10^{-4}$ ($3 \cdot 10^{-4}$)	0.50*** (0.04)	0.28*** (0.03)	-0.12 (0.07)	0.56
13	PZU	$2 \cdot 10^{-4}$ ($2 \cdot 10^{-4}$)	0.67*** (0.03)	0.12*** (0.02)	-0.08* (0.04)	0.73
14	Skarbiec	$-8 \cdot 10^{-5}$ ($3 \cdot 10^{-4}$)	0.47*** (0.03)	0.38*** (0.03)	0.02 (0.06)	0.51
15	UniKorona	$1 \cdot 10^{-4}$ ($3 \cdot 10^{-4}$)	0.47*** (0.03)	0.45*** (0.03)	-0.02 (0.06)	0.55

Note: The table is based on the entire sample P1; H-M (3) is the classical Henriksson-Merton model with the lagged excess return on market portfolio M as additional factor; the heteroskedastic consistent standard errors are in parentheses next to the coefficient estimates; the values of the adjusted determination coefficient are in the last column; * significant at the 10 per cent level; ** significant at the 5 per cent level; *** significant at the 1 per cent level.

The robust QML estimates of the parameters of the suitable GARCH(p, q) version of market-timing models are presented in Tables 6a–6b, respectively. It is worth stressing that some restrictions for the parameters in the GARCH(p, q) models (8) 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 nonnegative (Fiszeder, 2009). Note that in the case of all funds, both for the T-M model and for the H-M model the same variant of the GARCH(p, q) model has been chosen (Tables 6a–6b).

[2] When the values of the information criterions AIC or SC for different variants of the GARCH(p, q) models 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.

In summary, the results in Tables 5a–5b and 6a–6b clearly show that despite the strong ARCH effect in all models built based on the sample P1, the simpler robust HAC method is quite sufficient. Therefore, in our opinion, the GARCH(p, q) model is suitable but not necessary for such applications.

Table 6a. The GARCH(p, q) versions of the T-M market-timing models of Polish equity mutual funds in the entire period from Jan 2, 2003 to June 30, 2011

Fund. No.	T-M model – conditional mean equation				(p, q)	conditional variance equation				
	$\hat{\alpha}_P$	$\hat{\beta}_{1P}$	β_{2P}	$\hat{\gamma}_P$		$\hat{\alpha}_0$	α_1	$\hat{\alpha}_2$	$\hat{\beta}_1$	$\hat{\beta}_2$
1	$3\cdot10^{-4}$ $(1\cdot10^{-4})$	0.80 (0.01)	0.04 (0.01)	-1.60 (0.52)	(1,1)	$2\cdot10^{-7}$ $(1\cdot10^{-7})$	0.09 (0.02)	-	0.90 (0.02)	-
2	$3\cdot10^{-4}$ $(7\cdot10^{-5})$	0.86 (0.01)	0.01 (0.005)	-1.95 (0.33)	(1,2)	$2\cdot10^{-7}$ $(6\cdot10^{-8})$	0.47 (0.12)	-0.30 (0.12)	0.85 (0.03)	-
3	$-7\cdot10^{-5}$ $(5\cdot10^{-5})$	0.84 (0.005)	0.005 (0.004)	0.06 (0.18)	(1,1)	$7\cdot10^{-8}$ $(2\cdot10^{-8})$	0.08 (0.01)	-	0.91 (0.01)	-
4	$-1\cdot10^{-5}$ $(5\cdot10^{-5})$	0.89 (0.005)	0.003 (0.005)	0.06 (0.21)	(1,1)	$7\cdot10^{-8}$ $(2\cdot10^{-8})$	0.07 (0.01)	-	0.91 (0.01)	-
5	$7\cdot10^{-5}$ $(2\cdot10^{-4})$	0.34 (0.02)	0.25 (0.02)	-1.06 (1.07)	(2,2)	$4\cdot10^{-6}$ $(1\cdot10^{-6})$	0.17 (0.04)	0.20 (0.04)	-0.16 (0.05)	0.74 (0.05)
6	$-2\cdot10^{-4}$ $(9\cdot10^{-5})$	0.94 (0.03)	0.07 (0.02)	0.64 (0.69)	(1,2)	$4\cdot10^{-8}$ $(3\cdot10^{-8})$	0.28 (0.04)	-0.21 (0.04)	0.93 (0.01)	-
7	$-1\cdot10^{-4}$ $(7\cdot10^{-5})$	0.79 (0.01)	0.08 (0.01)	-0.28 (0.40)	(1,2)	$5\cdot10^{-8}$ $(3\cdot10^{-8})$	0.35 (0.04)	-0.26 (0.04)	0.91 (0.01)	-
8	$9\cdot10^{-5}$ $(6\cdot10^{-5})$	0.83 (0.007)	0.02 (0.005)	-0.009 (0.29)	(1,2)	$5\cdot10^{-8}$ $(2\cdot10^{-8})$	0.14 (0.03)	-0.07 (0.03)	0.93 (0.01)	-
9	$-2\cdot10^{-4}$ $(6\cdot10^{-5})$	0.81 (0.008)	0.009 (0.005)	$-2\cdot10^{-4}$ (0.31)	(2,1)	$8\cdot10^{-8}$ $(4\cdot10^{-8})$	0.13 (0.03)	-	0.33 (0.18)	0.54 (0.18)
10	$2\cdot10^{-5}$ $(1\cdot10^{-4})$	0.14 (0.08)	0.64 (0.04)	-0.89 (0.79)	(1,2)	$9\cdot10^{-8}$ $(6\cdot10^{-8})$	0.40 (0.07)	-0.30 (0.07)	0.91 (0.02)	-
11	$-2\cdot10^{-4}$ $(6\cdot10^{-5})$	0.89 (0.006)	0.02 (0.005)	-0.38 (0.28)	(2,1)	$9\cdot10^{-8}$ $(4\cdot10^{-8})$	0.13 (0.02)	-	0.39 (0.10)	0.47 (0.09)
12	$-4\cdot10^{-5}$ $(9\cdot10^{-5})$	0.73 (0.02)	0.06 (0.01)	-0.34 (0.52)	(1,2)	$6\cdot10^{-8}$ $(3\cdot10^{-8})$	0.27 (0.04)	-0.17 (0.03)	0.91 (0.01)	-
13	$-1\cdot10^{-4}$ $(5\cdot10^{-5})$	0.84 (0.005)	0.01 (0.004)	-0.17 (0.18)	(1,1)	$6\cdot10^{-8}$ $(2\cdot10^{-8})$	0.10 (0.02)	-	0.90 (0.02)	-
14	$2\cdot10^{-5}$ $(1\cdot10^{-4})$	0.42 (0.05)	0.41 (0.05)	0.35 (0.88)	(1,2)	$9\cdot10^{-7}$ $(4\cdot10^{-7})$	0.24 (0.04)	-0.16 (0.04)	0.91 (0.02)	-
15	$-6\cdot10^{-5}$ $(1\cdot10^{-4})$	0.40 (0.04)	0.53 (0.03)	0.80 (1.08)	(1,2)	$8\cdot10^{-7}$ $(5\cdot10^{-7})$	0.29 (0.03)	-0.20 (0.04)	0.90 (0.03)	-

Note: The table is based on the entire sample P1; T-M (2) is the classical Treynor-Mazuy model with the lagged excess return on market portfolio M as additional factor; the heteroskedastic consistent standard errors are in parentheses below the coefficient estimates; the variance-covariance matrix of the estimated parameters is based on the QML algorithm; the distribution for the innovations is supposed to be normal.

Table 6b. The GARCH(p, q) versions of the H-M market-timing models of Polish equity mutual funds in the entire period from Jan 2, 2003 to June 30, 2011

Fund. No.	H-M model – conditional mean equation				(p, q)	conditional variance equation				
	$\hat{\alpha}_P$	$\hat{\beta}_{1P}$	β_{2P}	$\hat{\gamma}_P$		$\hat{\alpha}_0$	α_1	$\hat{\alpha}_2$	$\hat{\beta}_1$	$\hat{\beta}_2$
1	$5\cdot10^{-4}$	0.75	0.04	-0.10	(1,1)	$2\cdot10^{-7}$	0.09	-	0.90	-
	$(1\cdot10^{-4})$	(0.02)	(0.01)	(0.03)		$(1\cdot10^{-7})$	(0.02)		(0.02)	
2	$8\cdot10^{-4}$	0.75	0.02	-0.18	(1,2)	$2\cdot10^{-7}$	0.52	-0.37	0.86	-
	$(7\cdot10^{-5})$	(0.03)	(0.005)	(0.03)		$(6\cdot10^{-8})$	(0.17)	(0.16)	(0.03)	
3	$-6\cdot10^{-5}$	0.83	0.005	$-4\cdot10^{-4}$	(1,1)	$7\cdot10^{-8}$	0.08	-	0.91	-
	$(7\cdot10^{-5})$	(0.008)	(0.004)	(0.01)		$(2\cdot10^{-8})$	(0.01)		(0.01)	
4	$-4\cdot10^{-5}$	0.89	0.002	-0.01	(1,1)	$7\cdot10^{-8}$	0.08	-	0.91	-
	$(7\cdot10^{-5})$	(0.009)	(0.005)	(0.01)		$(2\cdot10^{-8})$	(0.01)		(0.01)	
5	$2\cdot10^{-4}$	0.33	0.25	-0.06	(2,2)	$3\cdot10^{-8}$	0.20	-0.20	1.70	-0.70
	$(2\cdot10^{-4})$	(0.03)	(0.02)	(0.06)		$(1\cdot10^{-8})$	(0.04)	(0.04)	(0.06)	(0.05)
6	$-3\cdot10^{-4}$	0.97	0.07	0.05	(1,2)	$4\cdot10^{-8}$	0.29	-0.21	0.93	-
	$(1\cdot10^{-4})$	(0.03)	(0.02)	(0.04)		$(3\cdot10^{-8})$	(0.04)	(0.04)	(0.01)	
7	$-1\cdot10^{-4}$	0.78	0.08	-0.02	(1,2)	$5\cdot10^{-8}$	0.35	-0.25	0.91	-
	$(1\cdot10^{-4})$	(0.02)	(0.01)	(0.02)		$(3\cdot10^{-8})$	(0.04)	(0.04)	(0.01)	
8	$9\cdot10^{-5}$	0.83	0.02	$-8\cdot10^{-4}$	(1,2)	$6\cdot10^{-8}$	0.14	-0.07	0.93	-
	$(9\cdot10^{-5})$	(0.01)	(0.005)	(0.02)		$(2\cdot10^{-8})$	(0.03)	(0.03)	(0.01)	
9	$-7\cdot10^{-5}$	0.81	0.009	-0.02	(2,1)	$8\cdot10^{-8}$	0.13	-	0.32	0.54
	$(9\cdot10^{-5})$	(0.01)	(0.005)	(0.02)		$(4\cdot10^{-8})$	(0.03)		(0.18)	(0.18)
10	$-2\cdot10^{-4}$	0.14	0.65	0.02	(1,2)	$9\cdot10^{-8}$	0.39	-0.29	0.91	-
	$(1\cdot10^{-4})$	(0.06)	(0.05)	(0.04)		$(5\cdot10^{-8})$	(0.07)	(0.08)	(0.02)	
11	$-2\cdot10^{-4}$	0.88	0.02	-0.02	(2,1)	$9\cdot10^{-8}$	0.13	-	0.39	0.46
	$(8\cdot10^{-5})$	(0.01)	(0.005)	(0.02)		$(4\cdot10^{-8})$	(0.02)		(0.10)	(0.09)
12	$5\cdot10^{-5}$	0.71	0.06	-0.03	(1,2)	$6\cdot10^{-8}$	0.27	-0.18	0.91	-
	$(1\cdot10^{-4})$	(0.03)	(0.01)	(0.03)		$(3\cdot10^{-8})$	(0.03)	(0.03)	(0.01)	
13	$-2\cdot10^{-5}$	0.83	0.01	-0.02	(1,1)	$6\cdot10^{-8}$	0.10	-	0.90	-
	$(8\cdot10^{-5})$	(0.008)	(0.004)	(0.01)		$(3\cdot10^{-8})$	(0.02)		(0.02)	
14	$-1\cdot10^{-4}$	0.44	0.41	0.04	(1,2)	$9\cdot10^{-7}$	0.24	-0.16	0.91	-
	$(2\cdot10^{-4})$	(0.05)	(0.05)	(0.05)		$(4\cdot10^{-7})$	(0.04)	(0.04)	(0.02)	
15	$-2\cdot10^{-4}$	0.43	0.53	0.07	(1,2)	$9\cdot10^{-7}$	0.29	-0.20	0.90	-
	$(2\cdot10^{-4})$	(0.04)	(0.03)	(0.05)		$(5\cdot10^{-7})$	(0.03)	(0.04)	(0.03)	

Note: The table is based on the entire sample P1; H-M (3) is the classical Henriksson-Merton model with the lagged excess return on market portfolio M as additional factor; the heteroskedastic consistent standard errors are in parentheses below the coefficient estimates; the variance-covariance matrix of the estimated parameters is based on the QML algorithm; the distribution for the innovations is supposed to be normal.

Conclusions

Our research provides evidence of pronounced ARCH effects in the classical market-timing models of Polish open-end mutual funds. We detect for the ARCH effects in the entire period from Jan 2, 2003 to June 30, 2011, as well as for the 7 subperiods. For comparison, we estimate the market-timing models using two methods. Results on both the HAC and the GARCH estimates are qualitatively similar, and even better in the case of the simpler HAC method. For this reason, it is not necessary to estimate the GARCH versions of market-timing models in the case of Polish mutual funds, even despite the strong ARCH effects that exist in these models. As for the interpretation of the estimated coefficients, our empirical results can be summarized as follows:

1. There is no evidence that equity fund managers are successful in selectivity ($\hat{\alpha}_P$).
2. The levels of systematic risks are significantly positive ($\hat{\beta}_{1P}$).
3. The regressions including the lagged values of the market factor as an additional explanatory variable are well-founded (β_{2P}).
4. The empirical results show no statistical evidence that Polish equity fund managers have outguessed the market in the entire period Jan 2, 2003–June 30, 2011 ($\hat{\gamma}_P$).

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, a possible direction for further investigation would be the performance evaluation including the operating style and purpose of the funds as another factor (Wermers, 2000).

References

Adkins, L.C. (2010), *Using Gretl for Principles of Econometrics*, 3rd Edition, Version 1.313.

Bollen, N.P.B., Busse, J.A. (2001), On the Timing Ability of Mutual Fund Managers, *The Journal of Finance,* 56**(**3), 1075–1094.

Bollerslev, T. (1986), Generalized Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics,* 31, 307–327.

Bollerslev, T., Wooldridge, J.M. (1992), Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariances, *Econometric Reviews,* 11, 143–179.

Brzeszczyński, J., Gajdka, J., Schabek, T. (2011), The Role of Stock Size and Trading Intensity in the Magnitude of the „Interval Effect" in Beta Estimation: Empirical Evidence from the Polish Capital Market, *Emerging Markets Finance & Trade,* 47(1), 28–49.

Busse, J.A. (1999), Volatility Timing in Mutual Funds: Evidence from Daily Returns, *The Review of Financial Studies,* 12, 1009–1041.

Campbell, J.Y., Lo A.W., MacKinlay, A.O. (1997), *The Econometric of Financial Markets*, Princeton University Press, New Jersey.

Carhart, M.M. (1997), On Persistence in Mutual Fund Performance, *The Journal of Finance,* 52, 57–82.

Cogneau, P., Hübner, G. (2009), The 101 Ways to Measure Portfolio Performance, Working Paper, http://ssrn.com/abstract=1326076 (Sept 8, 2011).

Cohen, K.J., Hawawini, G.A., Maier, S.F., Schwartz, R.A., Whitcomb, D.K. (1980), Implications of Microstructure Theory for Empirical Research on Stock Price Behaviour, *The Journal of Finance,* 35, 249–257.

Dimson, E. (1979), Risk Measurement when Shares are Subject to Infrequent Trading, *Journal of Financial Economics,* 7, 197–226.

Doman, M., Doman, R. (2004), *Ekonometryczne modelowanie dynamiki polskiego rynku finansowego*, Wydawnictwo Akademii Ekonomicznej w Poznaniu, Poznań.

Doman, M. (2010), Liquidity and Market Microstructure Noise: Evidence from the Pekao Data, *Dynamic Econometric Models,* 10, 5–14.

Engle, R.F. (1982), Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflations, *Econometrica*, 50, 987–1007.

Engle, R.F. (ed.) (2000), *ARCH. Selected Readings*, Oxford University Press.

Fama, E.F., French, K.R. (1993), Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics,* 33, 3–56.

Fisher, L. (1966), Some New Stock Market Indexes, *Journal of Business,* 39, 191–225.

Fiszeder, P. (2009), *Modele klasy GARCH w empirycznych badaniach finansowych (The Class of GARCH Models in Empirical Finance Research),* Wydawnictwo Naukowe Uniwersytetu Mikołaja Kopernika, Toruń.

Ferson, W.E., Schadt R.W. (1996), Measuring Fund Strategy and Performance in Changing Economic Conditions, *The Journal of Finance,* 51, 425–461.

Greene, W.H. (2002), *Econometric Analysis*, Fifth Edition, Prentice Hall, New Jersey.

Hamilton, J.D. (2008), Macroeconomics and ARCH, Working Paper 14151, NBER Working Paper Series, Cambridge.

Henriksson, R., Merton, R. (1981), On Market Timing and Investment Performance. II. Statistical Procedures for Evaluating Forecasting Skills, *Journal of Business,* 54, 513–533.

Henriksson, R. (1984), Market Timing and Mutual Fund Performance: an Empirical Investigation, *Journal of Business,* 57, 73–96.

Jensen, M. (1968), The Performance of Mutual Funds in the Period 1945-1964, *The Journal of Finance,* 23, 389–416.

Kao, G.W., Cheng, L.T., Chan, K.C. (1998), International Mutual Fund Selectivity and Market Timing During Up and Down Market Conditions, *The Financial Review,* 33, 127–144.

Kufel, T. (2009), *Ekonometria. Rozwiązywanie problemów z wykorzystaniem programu Gretl,* PWN, Warszawa.

Lee, J. H. H. (1991), A Lagrange Multiplier Test for GARCH Models, *Economics Letters*, 37, 265–271.

Ljung, G., Box, G.E.P. (1978), On a Measure of Lack of Fit in Time Series Models, *Biometrika,* 66, 67–72.

Olbryś, J. (2012), Wieloczynnikowe hybrydowe modele market-timing polskich funduszy inwestycyjnych (Multifactor Hybrid Market-Timing Models of Polish Mutual Funds), *Studia Ekonomiczne – Zeszyty Naukowe,* Uniwersytet Ekonomiczny w Katowicach, accepted for publication.

Olbryś, J. (2011a), Book-to-Market, Size and Momentum Factors in Market-Timing Models: the Case of Polish Emerging Market, *Research in Economics and Business: Central and Eastern Europe,* Tallinn School of Economics and Business Administration of Tallinn University of Technology, 3(2), accepted for publication.

Olbryś, J. (2011b), The Intertemporal Cross Price Behavior and the "Fisher Effect" on the Warsaw Stock Exchange, *Ekonometria 31. Theory and Applications of Quantitative Methods. Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu,* accepted for publication.

Olbryś, J. (2010a), Orthogonalized Factors in Market-Timing Models of Polish Equity Funds, *Quantitative Methods in Economics*, WULS Press, 11(1), 128–138.

Olbryś, J. (2010b), Three-Factor Market-Timing Models with Fama and French's Spread Variables, *Operations Research and Decisions,* 2/2010, 91–106.

Olbryś, J. (2009), Conditional Market-Timing Models for Mutual Fund Performance Evaluation, *Prace i Materiały Wydziału Zarządzania Uniwersytetu Gdańskiego,* 4/2, 519–532.

Romacho, J.C., Cortez, M.C. (2006), Timing and Selectivity in Portuguese Mutual Fund Performance, *Research in International Business and Finance,* 20, 348–368.

Scholes, M., Williams, J. (1977), Estimating Betas from Nonsynchronous Data, *Journal of Financial Economics,* 5, 309–327.

Treynor, J., Mazuy, K. (1966), Can Mutual Funds Outguess the Market?, *Harvard Business Review,* 44, 131–136.

Tsay, R.S. (2010), *Analysis of Financial Time Series,* John Wiley, New York.

Wermers, R. (2000), Mutual Fund Performance: an Empirical Decomposition into Stock-Picking Talent, Style, Transaction Costs, and Expenses. *The Journal of Finance*, 55, 1655–1703.

Efekt ARCH w klasycznych modelach market-timing z opóźnioną zmienną rynkową: przypadek rynku polskiego

Z a r y s t r e ś c i. W artykule przedstawiono badania dokumentujące występowanie efektu ARCH w klasycznych modelach market-timing z opóźnioną zmienną rynkową w przypadku polskich funduszy akcji, w okresie styczeń 2003-czerwiec 2011. Dokonano estymacji wersji GARCH odpowiednich modeli oraz porównano jakość modeli GARCH i modeli uzyskanych metodą HAC. Wyniki wskazują, że modele GARCH są odpowiednie, ale metoda HAC jest wystarczająca, pomimo występowania efektu ARCH. Podano również interpretacje parametrów otrzymanych modeli w badanej grupie funduszy.

S ł o w a k l u c z o w e: model market-timing, niesynchroniczne transakcje, efekt ARCH, model GARCH.