EKONOMETRIA ECONOMETRICS 31 • 2011
ISSN 1507-3866

Joanna Olbryś
Bialystok University of Technology

THE INTERTEMPORAL CROSS PRICE BEHAVIOUR AND THE "FISHER EFFECT" ON THE WARSAW STOCK EXCHANGE[1]

Abstract: Market microstructure is now one of the most active research areas in economics and finance. Many authors point to various frictions in the trading process. It has been reported in the literature that some empirical phenomena can be attributed to these frictions. The main goal of this paper is to present the empirical results of testing such phenomena as the "Fisher effect", i.e. positive autocorrelation in market index returns and the intertemporal cross-correlations between pairs of securities' returns on the Warsaw Stock Exchange. According to the author's knowledge, the possible existence of such empirical phenomena in market indexes' returns and securities' returns has not yet been investigated on the WSE.

Key words: market microstructure, nonsynchronous trading, frictions, Fisher effect.

1. Introduction

Market microstructure is now one of the most active research areas in economics and finance. Many authors point to various frictions in the trading process. It has been reported in the literature that some empirical phenomena can be attributed to these frictions. In 1966 L. Fisher suggested that the market-index returns first-order autocorrelation was caused by a nonsynchronous trading of the component securities. "Nonsynchronous trading can introduce (a) lag-1 cross-correlation between stock returns, (b) lag-1 serial correlation in a portfolio return, and (c) in some situations negative serial correlations of the return series of a single stock" [Tsay 2010, p. 232]. The non-trading effect induces potentially serious biases in the moments and co-moments of asset returns such as their means, variances, co-variances, betas, and autocorrelation and cross-autocorrelation coefficients [Campbell, Lo, MacKinlay 1997, p. 84]. The main goal of this paper is to present the empirical results of testing such phenomena as the "Fisher effect", i.e., positive autocorrelation in market index returns, and the intertemporal cross-correlations between pairs of securities' returns on the Warsaw Stock Exchange.

[1] Financial support in 2009–2011 from the Polish Committee for Scientific Research within the grant No. N N113 173237 is gratefully acknowledged.

The paper is organized as follows. Section 1 provides a brief literature overview. In Section 2 we present the empirical results regarding the “Fisher effect” in market index returns and the intertemporal cross-correlations between pairs of securities' returns on the WSE.[2] Section 3 contains the main conclusions and goals for further investigation.

2. A brief literature review

The empirical market microstructure literature is an extensive one, straddling both academic and practical publications. For some purposes, such aspects of the market's 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 the most important [Campbell, Lo, MacKinlay 1997, p. 83]. In 1980 K.J. Cohen, G.A. Hawawini, S.F. Maier, R.A. Schwartz and D.K. Whitcomb 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 (e.g., [Dimson 1979; Fama 1970; Fisher 1966; Olbryś 2011; Perry 1985; Rosenberg, Rudd 1982; Roll 1981; Scholes, Williams 1977; Schwartz, Whitcomb 1977; Shanken 1987;]). Two common elements among most of the phenomena are evident, the intervaling effect and the impact of a security's “thinness”. In 1970 E.F. 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. G.A. Hawawini [1980a, b] found positive first-order cross-correlations between security returns. M. Scholes and J. Williams [1977] show how nonsynchronous security trading will induce spurious auto- and cross-correlations into individual security and market index returns. K.J. Cohen, S.F. Maier, R.A. Schwartz and D.K. Whitcomb [1986] place nonsynchronous trading in a broader class of market frictions, which may induce price-adjustment delays into the trading process [Atchison, Butler, Simonds 1987].

In [Cohen et al. 1980, p. 250] six empirical phenomena have been presented. For our present considerations, the most important of them are:

1) weak serial correlation in individual securities' daily returns,

2) positive serial cross-correlations between security returns and market index,

3) positive serial correlation in market index returns, with the smallest effect for long differencing intervals and those indexes giving the least weight to thin securities returns. This index phenomenon has been called the “Fisher effect” since Lawrence Fisher in 1966 hypothesized its probable cause.

Both statistical and microstructure explanations of the phenomena are reported in the literature. The statistical approaches have focused on the effect of serial cross-

[2] WSE – Warsaw Stock Exchange.

correlation among security returns, while the microstructure studies have also been concerned with frictions in the trading process. It has been shown in [Hawawini 1980a] that the existence of intertemporal (non-contemporaneous) cross-correlations between pairs of securities' returns is a sufficient condition to explain various phenomena reported in the literature such as positive autocorrelation in market indexes (i.e. the "Fisher effect"), the sensitivity of estimated systematic risk and others.

3. Empirical results on the Warsaw Stock Exchange

According to the author's knowledge, the possible existence of such empirical phenomena as the "Fisher effect" in market index returns and the intertemporal cross-correlations between pairs of securities' returns has not yet been investigated on the Warsaw Stock Exchange.

3.1. The dataset

To detect for the "Fisher effect" in the period investigated January 2, 2003 – June 30, 2010 (1884 observations), we study daily logarithmic returns on the Warsaw Stock Exchange indexes: WIG, WIG20, mWIG40 and sWIG80. We divide the whole sample into seven samples: P1, P2, P3, P4, P5, P6, P7 (see Table 1). In the next step we calculate partial autocorrelations functions (*PACF*).

To observe the presence of intertemporal cross-correlations between daily logarithmic returns on pairs of stocks we are not able to study the sWIG80-firms because of the very frequent rotation of firms in this index. Instead, we take the mWIG40-firms. Finally, the 17 common stocks listed on the WSE and entered into the mWIG40 over the whole period extending from January 2, 2008 to June 30, 2010 went into the database.

3.2. Evidence of the "Fisher effect" on the Warsaw Stock Exchange

As mentioned above, the evidence that daily market-index returns exhibit a pronounced positive first-order autocorrelation has been called the "Fisher effect" since L. Fisher in 1966 hypothesized its probable cause [Fisher 1966, pp. 205–208]. L. Fisher suggested it was caused by a nonsynchronous trading of the component securities. Fisher's explanation is bolstered by the fact that the observed correlation is higher in those indexes that give greater weight to the securities of smaller firms (which tend to be traded less frequently) [Perry 1985, p. 517].

"Positively auto-correlated market index returns could be generated (…) by the '(Lawrence) Fisher effect' mechanism: Suppose news occurs that would increase stock prices. But suppose that the prices of some stocks (group A) fully adjust by the close of trading on day j, while group B prices do not fully adjust until day $j + 1$. Then, *ceteris paribus*, the market index return will be positive on day j (because group A prices rise) and on day $j + 1$ (when group B prices complete their adjustment).

Hence, market index returns will be positively auto-correlated for daily (and longer) intervals" [Schwartz, Whitcomb 1977, p. 45].

To calculate partial autocorrelations functions (*PACF*), we first detect (based on the Dickey–Fuller test) that the analysed series: WIG, WIG20, mWIG40 and sWIG80 are stationary. Empirical values of the τ-statistic (at the 5% significance level) lie in the [–39.64; –31.59] interval and they are substantially lower than the critical value equal to –3.41.

In the next step we calculate partial autocorrelations functions (*PACF*) for individual stationary processes, in the seven samples P1, P2, P3, P4, P5, P6, P7 and we test the significance of the first-order daily serial correlation coefficients ρ_1 using the Quenouille's test [Kufel 2009, pp. 72–73]. Using the approximation that the standard error of the serial correlation coefficient is equal to $\frac{1}{\sqrt{n}}$, where n is the number of data points, the critical value of the Quenouille's test is equal to $\frac{u_a}{\sqrt{n}} = \frac{1.96}{\sqrt{n}}$. The evaluation of first-order serial correlation is carried out by testing the null hypothesis:

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

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

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

	n	Critical value of the Quenouille's test	WIG	WIG20	mWIG40	sWIG80
Sample P1 Jan 2, 2003 – June 30, 2010	1884	0.045	0.093	0.045	0.189	0.235
Sample P2 Jan 2, 2004 – June 30, 2010	1633	0.049	0.091	0.042	0.188	0.218
Sample P3 Jan 3, 2005 – June 30, 2010	1378	0.053	0.092	0.042	0.187	0.203
Sample P4 Jan 2, 2006 – June 30, 2010	1127	0.058	0.090	0.037	0.188	0.206
Sample P5 Jan 2, 2007 – June 30, 2010	876	0.066	0.090	0.036	0.181	0.185
Sample P6 Jan 2, 2008 – June 30, 2010	627	0.078	0.103	0.045	0.227	0.248
Sample P7 Jan 5, 2009 – June 30, 2010	376	0.101	0.119	0.073	0.196	0.197

Source: author's calculations (using *Gretl 1.8.5*).

The empirical results presented in Table 1 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 (1) only in the case of the WIG20 series.

3.3. The intertemporal cross price behaviour of common stocks on the Warsaw Stock Exchange

The presence of intertemporal cross-correlations in daily returns of securities is sufficient to explain various phenomena reported in the literature, for example the "Fisher effect". Fisher showed that the returns of stock market indexes exhibit positive autocorrelation even when they are constructed from individual securities which do not exhibit significant autocorrelations. This phenomenon can be attributed to the widespread existence of positive intertemporal cross-correlations among the securities that compose the index [Hawawini 1980a, p. 164].

Assuming stationarity, the autocorrelation coefficient of order *s* in the *M* index return can be written as [Hawawini 1980a]:

$$\rho_M^s = \frac{1}{\sigma_M^2} \cdot \left[\sum_{i=1}^{N} w_i^2 \cdot \sigma_i^2 \cdot \rho_i^s + \sum_{j=i+1}^{N} w_i \cdot w_j \cdot \sigma_{ij} \cdot q_{ij}^s \right], \quad (2)$$

where: w_i – the weight of the *i-th* security in the market index *M*, $i = 1, 2, \ldots, N$,

σ_i^2 – the variance of the *i*-th security returns,

σ_M^2 – the variance of the index returns,

ρ_i^s – the autocorrelation coefficient of order *s* in the *i*-th security returns,

σ_{ij} – the covariance between the *i*-th and *j*-th securities' returns,

ρ_{ij}^{+s} – the intertemporal cross-correlation coefficient of order +*s* for which the returns of the *i*-th security lead (+*s*) those of the *j*-th security,

ρ_{ij}^{-s} – the intertemporal cross-correlation coefficient of order –*s* for which the returns of the *i*-th security lag (–*s*) those of the *j*-th security,

σ_{ij} – the contemporaneous cross-correlation coefficient in the *i*-th and *j*-th securities' returns,

$q_{ij}^s = \frac{\rho_{ij}^{+s} + \rho_{ij}^{-s}}{\rho_{ij}}$ – the *q*-ratio of order *s* for the *i*-th and *j*-th securities, defined as the sum of lead and lag intertemporal cross-correlation coefficients of order *s* (for which the *i*-th security's returns lead and lag those of the *j*-th security, respectively), divided by the contemporaneous cross-correlation coefficient. The *q*-ratio is an appropriate measure of intertemporal cross dependence between two time-series [Hawawini 1980a, p. 155].

"It is clear from the equation (2) that as the number of securities (N) included in the index increases, the first term becomes negligible in comparison to the second. This is because the number of intertemporal cross-correlations rises much faster than the number of autocorrelations as N increases" [Hawawini 1980a, p. 164].

It has been shown in [Hawawini 1980a, p. 165] that since the daily first-order q-ratios of *NYSE* securities were found to be, in general, positive, it follows that the daily returns on an *NYSE* index should display positive first-order autocorrelation. Therefore, we compute the q-ratios of order 1 for all pairs of securities:

$$q_{ij}^{1} = \frac{\rho_{ij}^{+1} + \rho_{ij}^{-1}}{\rho_{ij}}, \tag{3}$$

where ρ_{ij}^{+1}, ρ_{ij}^{-1}, ρ_{ij} are as in the equation (2).

The q-ratio of order $s = 1$ is a measure of the first-order intertemporal cross-correlation coefficient of order $s = 1$ per unit of contemporaneous cross-correlation.

The following equations are obvious:

$$\rho_{ij}^{+1} = \rho_{ji}^{-1}, \rho_{ij}^{-1} = \rho_{ji}^{+1}. \tag{4}$$

Therefore

$$q_{ij}^{1} = \frac{\rho_{ij}^{+1} + \rho_{ji}^{+1}}{\rho_{ij}} \quad \text{or} \quad q_{ij}^{1} = \frac{\rho_{ij}^{-1} + \rho_{ji}^{-1}}{\rho_{ij}} \tag{5}$$

and

$$q_{ii}^{1} = \frac{\rho_{ii}^{+1} + \rho_{ii}^{-1}}{\rho_{ii}} = 2 \cdot \rho_{ii}^{+1} = 2 \cdot \rho_{ii}^{-1}. \tag{6}$$

Table 2 presents the intertemporal cross-correlation coefficients $\rho_{ij}^{+1}, \rho_{ji}^{+1}$ between pairs of the mWIG40 securities in the P6 sample in the period from Jan 2, 2008 to June 30, 2010 (see Table 1). In this period the value of the *PACF* for the mWIG40 index is the greatest. The important results of Table 2 can be summarized as follows. First, the intertemporal cross-correlations are generally positive. Second, these correlations are generally stronger and more prevalent for the j-th securities (in equations (4)). Third, they are never stronger than their corresponding contemporaneous cross-correlation coefficients ρ_{ij} (see Table 3 for details). All contemporaneous cross-correlations are significantly different from zero.

Table 4 presents the q-ratios of order $s = 1$ as the measures of first-order intertemporal cross-correlation coefficients of order $s = 1$ per unit of contemporaneous cross-correlations, between pairs of the mWIG40 stocks in the period from January 2, 2008 to June 30, 2010 (based on equation (5)). The q-ratios are generally positive, ranging from –0.235 (for NET and BDX) to 2.149 (for MMP and EAT). These values are negative only in five cases: (CCC, CCC), (ORB, ORB), (NET, BDX), (NET,

Table 2. Evidence of intertemporal cross-correlation coefficients $\rho_{ij}^{+1}, \rho_{ji}^{+1}$ between the mWIG40 securities (the period from January 2, 2008 to June 30, 2010)

j \ i	EAT	BDX	CCC	ECH	EMP	GNT	BHW	BSK	KTY	KPX	LPP	MIL	MMP	NET	ORB	STP	SNS	%
EAT	0.104	0.025	0.049	0.068	0.077	–0.036	–0.029	0.075	0.015	0.000	0.061	–0.018	0.134	–0.009	–0.037	0.040	–0.055	11.8%
BDX	0.064	0.034	0.072	0.063	0.035	0.066	0.027	0.069	0.017	0.032	0.043	0.061	0.034	–0.051	–0.018	0.044	0.070	0%
CCC	0.052	0.030	–0.083	–0.041	0.032	–0.062	0.027	0.055	0.003	–0.033	–0.013	–0.038	0.061	0.084	0.028	–0.034	–0.074	11.8%
ECH	0.110	0.044	0.080	0.099	0.088	0.087	0.078	0.131	0.072	0.073	0.085	0.061	0.162	0.040	0.085	0.050	0.047	58.8%
EMP	0.144	0.041	0.051	0.068	0.095	0.007	0.031	0.042	0.095	0.028	0.136	0.009	0.081	–0.025	0.022	0.027	–0.024	29.4%
GNT	0.154	0.131	0.085	0.149	0.163	0.117	0.077	0.091	0.139	0.086	0.124	0.062	0.111	0.055	0.049	0.059	–0.020	70.6%
BHW	0.035	0.082	0.133	0.006	0.084	0.001	0.094	0.083	0.077	0.051	0.036	0.026	0.130	0.090	0.019	0.030	–0.010	47.1%
BSK	0.127	0.023	0.052	0.092	0.082	0.010	0.098	0.138	0.059	0.071	0.100	0.080	0.121	0.014	0.025	0.056	0.032	47.1%
KTY	0.069	–0.014	0.122	0.056	0.090	0.024	0.031	0.051	0.062	0.049	0.056	0.018	0.098	0.021	0.065	0.062	–0.027	17.6%
KPX	0.149	0.090	0.066	0.096	0.169	0.124	0.132	0.123	0.177	0.179	0.141	0.054	0.131	0.059	0.068	0.088	–0.012	70.1%
LPP	0.035	–0.016	0.133	0.006	0.084	0.001	0.061	0.083	0.077	0.051	0.036	0.026	0.130	0.090	0.019	0.030	–0.010	35.3%
MIL	0.205	0.127	0.138	0.123	0.102	0.083	0.167	0.223	0.096	0.109	0.035	0.175	0.181	0.043	0.069	0.030	0.026	70.1%
MMP	0.169	–0.009	0.041	0.085	0.072	0.020	–0.045	0.074	0.080	0.004	0.024	–0.004	0.012	0.051	0.055	0.033	–0.033	17.6%
NET	0.047	0.016	–0.008	0.117	–0.007	0.096	0.044	0.070	0.080	0.129	–0.039	0.025	0.052	0.018	0.026	0.055	–0.010	23.5%
ORB	0.090	0.032	0.061	0.082	0.032	0.049	0.015	0.107	0.035	0.066	0.022	0.047	0.082	–0.049	-0.020	0.019	0.011	23.5%
STP	0.116	0.082	0.036	0.138	0.114	0.119	0.129	0.085	0.142	0.183	0.045	0.111	0.061	0.077	0.060	0.088	0.004	70.6%
SNS	0.111	0.089	0.077	0.085	0.125	0.089	0.123	0.174	0.098	0.132	0.064	0.112	0.129	0.070	0.068	0.072	0.068	70.6%
% of significant correlation	64.7%	35.3%	47.1%	58.8%	64.7%	41.2%	47.1%	58.8%	58.8%	35.3%	29.4%	23.5%	70.6%	23.5%	5.9%	11.8%	0%	

The critical value $r^* = 0.078$.

Source: author’s calculations (using *Excel*).

Table 3. Evidence of contemporaneous cross-correlation coefficients ρ_{ij} between the mWIG40 securities (the period from January 2, 2008 to June 30, 2010)

j \ i	EAT	BDX	CCC	ECH	EMP	GNT	BHW	BSK	KTY	KPX	LPP	MIL	MMP	NET	ORB	STP	SNS
EAT	1																
BDX	0.250	1															
CCC	0.223	0.207	1														
ECH	0.317	0.269	0.251	1													
EMP	0.256	0.197	0.196	0.222	1												
GNT	0.289	0.318	0.184	0.397	0.293	1											
BHW	0.313	0.352	0.202	0.319	0.264	0.422	1										
BSK	0.338	0.308	0.261	0.386	0.277	0.355	0.420	1									
KTY	0.261	0.308	0.204	0.325	0.339	0.354	0.369	0.299	1								
KPX	0.329	0.332	0.169	0.411	0.322	0.545	0.441	0.369	0.339	1							
LPP	0.183	0.194	0.193	0.146	0.271	0.208	0.227	0.230	0.309	0.241	1						
MIL	0.345	0.330	0.260	0.383	0.223	0.425	0.473	0.468	0.295	0.458	0.208	1					
MMP	0.141	0.250	0.187	0.207	0.248	0.232	0.251	0.244	0.246	0.226	0.185	0.243	1				
NET	0.095	0.149	0.145	0.186	0.187	0.221	0.239	0.172	0.255	0.232	0.158	0.191	0.174	1			
ORB	0.190	0.230	0.163	0.260	0.245	0.258	0.217	0.287	0.240	0.226	0.197	0.281	0.163	0.197	1		
STP	0.190	0.210	0.138	0.264	0.315	0.297	0.257	0.254	0.271	0.342	0.222	0.289	0.188	0.224	0.213	1	
SNS	0.274	0.348	0.210	0.359	0.179	0.390	0.355	0.364	0.301	0.397	0.268	0.395	0.184	0.148	0.163	0.260	1

The critical value $r^* = 0.078$.

Source: author's calculations (using *Excel*).

Table 4. Evidence of q-ratios of order $s = 1$ $q_{ij}^{1} = \frac{\rho_{ij}^{+1} + \rho_{ji}^{+1}}{\rho_{ij}}$ between the mWIG40 securities (the period from January 2, 2008 to June 30, 2010)

j \ i	EAT	BDX	CCC	ECH	EMP	GNT	BHW	BSK	KTY	KPX	LPP	MIL	MMP	NET	ORB	STP	SNS
EAT	0.208																
BDX	0.356	0.068															
CCC	0.453	0.453	–0.166														
ECH	0.562	0.398	0.155	0.198													
EMP	0.863	0.386	0.423	0.703	0.190												
GNT	0.408	0.619	0.125	0.594	0.935	0.234											
BHW	0.019	0.310	0.792	0.263	0.436	0.185	0.188										
BSK	0.598	0.299	0.410	0.578	0.448	0.285	0.431	0.276									
KTY	0.322	0.010	0.613	0.394	0.546	0.460	0.293	0.368	0.124								
KPX	0.453	0.367	0.195	0.411	0.612	0.385	0.415	0.526	0.667	0.358							
LPP	0.525	0.139	0.622	0.623	0.812	0.601	0.427	0.796	0.430	0.797	0.072						
MIL	0.542	0.570	0.385	0.480	0.498	0.341	0.408	0.647	0.386	0.356	0.293	0.350					
MMP	2.149	0.100	0.545	1.193	0.617	0.565	0.339	0.799	0.724	0.597	0.832	0.728	0.024				
NET	0.400	–0.235	0.524	0.844	–0.171	0.683	0.561	0.488	0.396	0.810	0.323	0.356	0.592	0.036			
ORB	0.279	0.061	0.546	0.642	0.220	0.380	0.157	0.373	0.417	0.593	0.208	0.413	0.840	–0.117	–0.040		
STP	0.821	0.600	0.014	0.712	0.448	0.599	0.619	0.555	0.753	0.792	0.338	0.488	0.500	0.589	0.371	0.176	
SNS	0.204	0.457	0.014	0.368	0.564	0.177	0.318	0.566	0.236	0.302	0.201	0.349	0.522	0.405	0.485	0.292	0.136

Source: author's calculations (using *Excel*).

EMP) and (NET, ORB). The q-ratios are greater than one only in the case of pairs: (MMP, EAT) and (MMP, ECH). Since the daily first-order q-ratios of the mWIG40 securities were found to be, in general, positive, it follows that the daily logarithmic returns on the mWIG40 index should display a positive first-order autocorrelation (based on (2)).

4. Conclusions

The empirical results show a pronounced "Fisher effect" in the case of the WIG, mWIG40 and sWIG80 series. This evidence is consistent with most of the literature on frictions in the trading process. Frictions in the trading process have an intricate and pervasive impact on the returns generation process [Cohen et al. 1980, p. 256]. L. Fisher suggested that the market-index returns first-order autocorrelation was caused by a nonsynchronous trading of the component securities. A nonsynchronous trading problem probably exists on the WSE. For this reason, for example, we could use Dimson's correction [Dimson 1979] and include lagged values of the market factors as additional independent variables in the regressions of market-timing models of Polish equity mutual funds to accommodate infrequent trading [Busse 1999; Olbryś 2010]. A possible direction for further investigation would be a multifactor market-timing model with lagged market factor.

References

Atchison M., Butler K., Simonds R., Nonsynchronous security trading and market index autocorrelation, *The Journal of Finance* 1987, Vol. 42, pp. 111–118.

Busse J.A., Volatility timing in mutual funds: Evidence from daily returns, *The Review of Financial Studies* 1999, Vol. 12, No. 5, pp. 1009–1041.

Campbell J.Y., Lo A.W., MacKinlay A.C., *The Econometrics of Financial Markets*, Princeton University Press, Princeton, NJ, 1997.

Cohen K.J., Hawawini G.A., Maier S.F., Schwartz R.A., Whitcomb D.K., Implications of microstructure theory for empirical research on stock price behaviour, *The Journal of Finance* 1980, Vol. 35, pp. 249–257.

Cohen K.J., Maier S.F., Schwartz R.A., Whitcomb D.K., *The Microstructure of Security Markets: Theory and Implications*, Prentice-Hall, Englewood Cliffs, NJ, 1986.

Dimson E., Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* 1979, Vol. 7, pp. 197–226.

Fama E.F., Efficient capital markets: A review of theory and empirical work, *The Journal of Finance* 1970, Vol. 15 (May), pp. 383–417.

Fisher L., Some new stock market indexes, *Journal of Business* 1966, Vol. 39, pp. 191–225.

Hawawini G.A., The intertemporal cross price behavior of common stocks: evidence and implications, *Journal of Financial Research* 1980a, Vol. 3, pp. 153–167.

Hawawini G.A., Intertemporal cross dependence in securities daily returns and the short run intervaling effect on systematic risk, *Journal of Financial and Quantitative Analysis* 1980b, March, pp. 139–149.

Kufel T., *Ekonometria. Rozwiązywanie problemów z wykorzystaniem programu Gretl*, Wydawnictwo Naukowe PWN, Warszawa 2009.

Olbryś J., Three-factor market-timing models with Fama and French's spread variables, *Operations Research and Decisions* 2010, Vol. 2, pp. 91–106.

Olbryś J., Problem danych niesynchronicznych w modelach market-timing, [in:] *Klasyfikacja i analiza danych – teoria i zastosowania*, Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu nr 176, Taksonomia 18, UE, Wrocław 2011, pp. 522–530.

Perry P.R., Portfolio serial correlation and nonsynchronous trading, *Journal of Financial and Quantitative Analysis* 1985, Vol. 20, pp. 517–523.

Roll R., A possible explanation of the small firm effect, *The Journal of Finance* 1981, Vol. 36, pp. 879–888.

Rosenberg B., Rudd A., Factor-related and specific returns of common stocks: serial correlation and market inefficiency, *The Journal of Finance* 1982, Vol. 37, pp. 543–554.

Scholes M., Williams J., Estimating betas from nonsynchronous data, *Journal of Financial Economics* 1977, Vol. 5, pp. 309–327.

Schwartz R., Whitcomb D., The time-variance relationship: evidence on autocorrelation in common stock returns, *Journal of Finance* 1977, March, pp. 41–55.

Shanken J., Nonsynchronous data and the covariance-factor structure of returns, *The Journal of Finance* 1987, Vol. 42, pp. 221–232.

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

MIĘDZYOKRESOWE ZALEŻNOŚCI CEN AKCJI ORAZ „EFEKT FISHERA" NA GPW W WARSZAWIE

Streszczenie: Jednym ze stosunkowo nowych kierunków badań nad istotą procesów finansowych jest analiza mikrostruktury rynku. Badane zagadnienia związane z tym tematem obejmują m.in. konsekwencje występowania tzw. tarć w procesie transakcyjnym. Są one przyczyną empirycznych anomalii w szeregach stóp zwrotu akcji oraz indeksów giełdowych. Celem artykułu jest prezentacja wyników badań empirycznych dotyczących międzyokresowych zależności cen akcji oraz tzw. efektu Fishera w szeregach dziennych logarytmicznych stóp zwrotu indeksów na GPW w Warszawie. Według wiedzy autorki występowanie wymienionych anomalii nie zostało do tej pory zdiagnozowane w przypadku polskiego rynku giełdowego.

Słowa kluczowe: mikrostruktura rynku, niesynchroniczne transakcje, tarcia, efekt Fishera.