






“Measuring investors’ emotions using econometric models of trading volume of stock exchange indexes”

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MEASURING INVESTORS' EMOTIONS USING ECONOMETRIC MODELS OF TRADING VOLUME OF STOCK EXCHANGE INDEXES¹

Abstract

Traditional finance explains all human activity on the ground of rationality and suggests all decisions are rational because all current information is reflected in the prices of goods. Unfortunately, the development of information technology and a growth of demand for new, attractive possibilities of investment caused the process of searching new, unique signals supporting investment decisions. Such a situation is similar to risk-taking, so it must elicit the emotional reactions of individual traders.

The paper aims to verify the question that the market risk may be the determinant of traders' emotions, and if volatility is a useful tool during the investment process as the measure of traders' optimism, similarly to Majewski's work (2019). Likewise, various econometric types of models of estimation of the risk parameter were used in the research: classical linear using OLS, general linear using FGLS, and GARCH(p, q) models using maximum likelihood method. Hypotheses were verified using the data collected from the most popular world stock exchanges: New York, Frankfurt, Tokyo, and London. Data concerned stock exchange indexes such as SP500, DAX, Nikkei, and UK100.

Keywords

heuristics, investors' psychology, financial econometrics, behavioral finance

JEL Classification

D91, G41, C58

INTRODUCTION

Stock exchanges are the most significant institutions forming virtual safety platforms of financial assets trading. They guarantee the safety of transactions and anonymity for investors, on the one hand, and transparency, on the other hand. It is one of the reasons why investors use the stock exchange market as a possibility of earning money. During years, investors have created some practices, which became quasi-official rules. Therefore, every ordinary investor knows, for example, the law that the stock exchange trading volume mirrors market trends and gives the confirmation signals obtained from technical analysis. So, every emotional decision of the stock exchange investor is immediately reflected in a trading volume. The article proposes calculating logarithmic changes in trading volume to observe not a state but the dynamics of investors' behavior. Just now, it is possible to see the excessive movement of trading volume changes supposing they describe the emotional state of investors' minds.

Emotions are state of the human mind, extremely mean in two opposite aspects: optimism and pessimism. The optimism is a term taken from psychology describing the belief of humans in success or hope-

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fulness and confidence during the process of decision making, according to Majewski (2019). On the other hand, pessimism means an expectation of bad things to happen or something not successful.

Kahneman and Tversky (1979) described psychology's role in economic activities in their "prospect theory". This role, especially for investors, was changed diametrically. The works of these two psychologists had a strong influence on academic studies and individuals' judgment. Entering terms "heuristics and biases" to economic theories helped explain errors in theoretical models describing the influence of psychology on traders' activity, according to Gilovich, Griffin, and Kahneman (2002).

1. LITERATURE REVIEW

Investing in stock exchanges for the first look does not involve specialized knowledge from individual investors. Usually, they think that the most important is to have an intuition. The experimental work of Czekaj, Markiewicz, Kubinska, and Czapryna (2016) showed that new investors believe that technical analysis is not such an effective supporting investment decision regarding the market experience and the intuition. On the other hand, professional traders of futures market still support their investment decisions using technical analysis. In the paper, technical analysis is treated as proof for existing emotional reactions, belief in a self-fulfilling prophecy, and other market irrational phenomena. Czekaj, Kubinska, Markiewicz, and Czapryna (2016) conclude, based on their experiments, that the technical analysis is the most popular method supporting investment decisions between futures traders.

The technical analysis's major application is the anticipating of trends in the stock prices using historical data. According to Majewski (2019), "It relies on that markets discount everything except information generated by market action". It means that the anticipation process needs only data generated by the market (Sewell, 2007).

The problem of separating optimistic and pessimistic signals appears here. During the noticeable trends, one can assume that the beliefs of traders in their continuing are exactly described by trading volume. Therefore, this indicator allows uncovering such emotions as optimism and pessimism (Majewski, 2019). However, emotions accompany investors' every decision, not only during clear trends. Therefore, the authors consider additional various-time-length volatility representing the standard deviation (30-, 90-, and 180-days) to eliminate even little emotional reactions.

Many authors suggest that technical analysis should be improved by using automated algorithms and that the traditional patterns such as head-and-shoulders and rectangles, although sometimes efficient, are not optimal, like in the research of Lo, Mamaysky, and Wang (2002). Some of them claim that technical analysis today is neither more important nor less than before and could be called the "workhorse" of currency exchange, as in Gehrig and Menkhoff (2006).

The authors surveyed approximately 200 FX in Austria and Germany in 1992 and 2002. The analysis allowed them to create general five conclusions supporting using technical analysis as a decision-making method. The most important are as follows:

- technical analysis has a complementary use;
- technical analysis is an instrument for short-term forecasting;
- fund managers use the three types of information distinguished in a similar pattern as FX dealers but with longer horizons;
- chartists still believe in the importance of market psychology.

However, there is also a big group of investors indicating a weakness in technical analysis. Very often, they list such kinds of problems as follows:

- even the best method of technical analysis cannot reliably predict the future, and signals flowing from some indicators are strongly delayed (e.g., from moving averages);
- tools are available to everyone so that nobody could gain an advantage over the other investors;

- interpretation is more art than science (often it is based on the analyst's image than the transparent normative).

The answers to why so significant number of investors believe in technical analysis are usually hidden in the psychology of human activity. Sewell (2007) presents the major of them:

1. Communal reinforcement is the social construction consisting of forming common beliefs based on repeated opinions by stock exchange investors in isolation from empirical evidence, according to Carroll (2003).
2. Selective thinking is the process of evidence selection consisting of the preference of proofs confirming the thesis adopted earlier while ignoring this, which are inconsistent with it.
3. One of the heuristics, which is closely tied with the selective thinking process, is confirmation bias. It is a tendency seeking of information confirming existing beliefs and ignoring everything contrary to them. A literature review distinguishes two kinds of meanings for this term. The first meaning concerns confirmation acquired information, but the second is the verification method basing only on confirmatory cases ignoring these unfavorable (confirmatory strategy of testing hypothesis) like in the research of Majewski (2019).
4. Self-deception is considered a widespread phenomenon according to the work of Bortolotti and Mameli (2012). The term focuses beliefs acquired and held despite strong evidence, and which are motivated by desires and emotions, according to DeWeese-Boyd (2007).

It could be concluded that many investors' reasons for using technical analysis despite facts proving its low efficiency have their roots in human behavior. On the one hand, it is possible to explain the causes of the irrational behavior of investors. On the other hand, it is also a reason for other biases observed in behavioral economics. First of all, using technical analysis by investors drives to the illusion of control, known as a self-fulfilling prophecy like Murphy's work (1999). Generally, the term "illusion of control" is defined as overestimation of ex-

pected the event likelihood relative to its objective probability, according to Langer (1975). Sometimes, investors find out that they are not efficient despite their believing in the rightness of their decisions. Then the illusion of control is replaced by faith in "the wheel of fortune" and "regression to the average". However, these beliefs are not supported by any reasonable shreds of evidence. At this point, it should be emphasized that both the causes and the effects of using technical analysis by investors belong to the same group of factors. Most of them can be classified as cognitive biases based on greed and fear. Many phenomena and heuristics influence investors, confirming their belief in technical analysis and hiding behind the concept of cognitive biases. Behavioral finance literature distinguishes, among the others, the following types of phenomena in this area (Thaler, 2005):

- overconfidence;
- confirmation;
- representativeness;
- anchoring effect;
- hindsight.

The paper aims to verify the scientific problem that the market risk may be the determinant of traders' emotions, so it could be used during the investment process to indicate investors' emotions according to technical analysis (TA). Rules of TA dictate the confirmation of the truthfulness of signals deriving from historical prices by changes in trading volume. The convergence of changes' directions confirms continuity of trend and the divergence – the change of market trends. The major hypothesis is that stock exchange trading volume reflects investors' emotions supporting financial decisions by its econometric models. The assumption follows the work of Majewski (2019), that "trading volume could be modeled by market risk" represented by "standard deviation of rates of return". The biggest and most popular stock exchanges were chosen to verify a raised hypothesis. Quotations of popular stock exchange indexes were used in the research. They are the following indexes: Standard and Poor's 500 (S&P500), Nikkei heikin kabuki (NIKKEI 225), Deutscher Aktienindex (DAX), Financial Times Stock Exchange (FTSE 100). Data for analysis were collected in the following periods: from 26th May 1998 for S&P (5,411 observations), 6th June 2002 for DAX (4,392 observations), and FTSE (4,370 ob-

servations), and from 4th March 2003 for NIKKEI (4,057 observations). Various types of econometric models were used, but the best approximations were obtained for dynamic econometric models of the type (G)ARCH. It is widely known in econometrics that different length of periods for standard deviation calculating influence on the results. Therefore, this problem was taken into account. The estimation results indicated that in the case of stock exchange indexes, the best approximations had been obtained for 30-days periods in contrast to the work of Majewska (2000).

2. METHODS AND HYPOTHESES

There are many different methods focused on sentiment measuring. Some of them were described in the work of Bandopadhyaya and Jones (2006). Their article presents the essential works on the sentiment measuring divided into the parts according to research. They could be listed as follows:

1. Optimism/pessimism about the economy:

- Index of Consumer Confidence measured by Survey by Conference Board, according to Fisher and Statman (2003) – www.conference-board.org;
- Consumer Confidence Index measured by Monthly Survey by the University of Michigan, according to and Fisher and Statman (2003).

2. Optimism/pessimism about the stock market:

- Put/Call Ratio (PCR) by Dennis and Mayhew (2002):

$$PCR = \frac{PO}{CO}, \quad (1)$$

where PO – put outstanding, CO – call outstanding;

- Trin. statistic:

$$TRIN = \frac{\frac{VDI}{NDI}}{\frac{VAI}{NAI}}, \quad (2)$$

- where VDI – volume of decline issues, NDI – number of decline issues, VAI – volume of decline issues, NAI – number of decline issues.

The statistic has not any academic references.

- Mutual Funds Cash Positions – % of cash held in Mutual Funds by Gup (1973) and net cash flow into Mutual Funds by Randall, Suk, and Tully (2003);
- Mutual Fund redemptions by Neal and Wheatley (1998):

$$MFr = \frac{NR}{TA}, \quad (3)$$

where NR – net redemptions, TA – total assets;

- AAI Survey was measured by a survey of individual investors by Fisher and Statman (2000, 2003);
- Investors Intelligence Survey measured by a survey of newsletter writers by Fisher and Statman (2000);
- Barron's Confidence Index by Lashgari (2000):

$$Baron's CI = Y_{AAA} - Y_{BBB}, \quad (4)$$

where Y – yield type AAA or BBB .;

- TED spread by Lashgari (2000):

$$TED = TFY - EFY, \quad (5)$$

where TFY – Treasury futures yield, EFY – Eurodollar futures yield;

- Merrill Lynch Survey measured by Wall Street sell-side analysts survey, according to Fisher and Statman (2000, 2003).

3. The riskiness of the stock market:

Insurance ratio by Baker and Wurgler (2006):

$$Ins = \frac{GAE}{GADE}, \quad (6)$$

where *Ins* – insurance [%], *GAE* – gross annual equities issued, *GADE* – gross annual debt and equities issued;

- RIPO – average annual first-day returns on IPOs by Baker and Wurgler (2006);
- Turnover by Baker and Wurgler (2006):

$$T = \frac{RSV}{ASL}, \quad (7)$$

where *T* – turnover, *RSV* – reported shares volume, *ASL* – average shares listed on NYSE (logged and detrended);

- Close-ended fund discount – *Y/E*, the value-weighted average discount on close-ended according to Baker and Wurgler (2006), Neal and Wheatley (1998), Lee, Schleifer, and Thaler (1991), and Chopra, Lee, Schleifer, and Thaler (1993);
- Market liquidity by Baker and Stein (2002):

$$ML = \frac{RSV}{ANS}, \quad (8)$$

where *ANS* – average number of shares;

- NYSE seat prices – Trading volume or quoted bid-ask spread by Keim and Madhavan (2000).
- The riskiness of the individual stock:
 - Beta (β) – CAPM.
 - Risk aversion:
 - Risk Appetite Index – Spearman Rank correlation volatility vs excess returns, according to Kumar and Persaud (2002);
 - VIX (Investors Fear Gauge) – implied options volatility by Whaley (2000).

There are also some other works taking into account optimism, but their point of view is not so general as in the case of measures standing above. There could be such measures as, for example:

- analyst's optimism for earnings forecasts, according to Nianhang, Xuanyu, Kam, and Zhihong (2013):

$$FB_{i,j,T,t} = \frac{AF_{i,j,T,t} - EPS_{i,t}}{P_{i,T-1}}, \quad (9)$$

where *FB* – forecast bias, *AF* – analysts' forecast, *EPS* – actual earnings-per-share ratio, *P* – price;

- managerial optimism, according to Yueh-hsiang, Shing-yang, and Ming-shen (2005):

$$I_{it} = \beta_1 + \beta_2 C_{it} + \beta_3 Q_{it-1} + \beta_4 O_i + \beta_5 C_{it} Q_{it-1} + \beta_6 C_{it} O_i + \varepsilon_{it}, \quad (10)$$

where *I* – investment, *C* – cash flow from the operation, $Q = MV / BV$, *MV* – market value, *BV* – book value, *O* – dummy variable (representing optimism measure);

- Testing optimism by measuring the relations between market ratios or parameters like stock dividends, splits, trading volume, and volatility, according to Crawford, Franz, and Lobo (2005).

It is worth noting that all of these studies are based on three groups of methods:

- survey analysis;
- descriptive statistics – statistical analysis of indicators;
- correlation or regression analysis.

In the presented approach, there is a proposition to use econometric models to identify a correlation between some significant factors influencing individual and institutional investors' emotions. The research's core point is focused on the econometric analysis using classical econometric models and dynamic autoregressive models. The idea is based on the assumption that the volatilities of rates of return (risk parameters) and trading volume (logarithms of changes) are significantly correlated, according to Majewski (2019). In the paper was assumed that:

- changes in trading volume illustrate investors' emotions;

- volatility reflects the trading activity of stock exchange investors;
- short-time (30 trading days) volatility has better cognitive features for econometric modeling than longer one;
- every abnormal (emotional) activity of traders (expressed by volatility) has a significant influence on changes in trading volume;
- one-day-in-a-week (calendar effects) are also taken into account in econometric models' specifications.

The study presents two research hypotheses:

- H1: 30-days trading volatility has the most significant influence on traders' emotions (measured by trading volatility).*
- H2: The best approximation describing changes in trading volume is obtained using (G) ARCH models regarding calendar effects.*

The research was conducted in the following steps:

- data collection;
- model estimation;
- selection of the best model.

The logarithmic changes of trading volume of stocks exchange indexes are described by: R_t – stock exchange indexes' rates of return, R_{t-i} – rates of return of the stock exchange index with i -days time-lag, Mo – Monday (dummy variable), Tu – Tuesday (dummy variable), We – Wednesday (dummy variable), Th – Thursday (dummy variable), Fr – Friday (dummy variable), $V30_t$ – 30-days-volatility without time-lag, $V30_{t-i}$ – 30-days-volatility with i -days time-lag, $V90_t$ – 90-days-volatility without time-lag, $V90_{t-i}$ – 90-days-volatility with i -days time-lag, $V180_t$ – 180-days-volatility without time-lag, $V180_{t-i}$ – 180-days-volatility with i -days time-lag.

The base equation for the estimation of logarithmic changes in trading volume is as follows:

$$y_t = \gamma_0 + \sum_{k=1}^n \gamma_k X_{kt} + \varepsilon_t, \quad (11)$$

where y_t – logarithmic changes of trading volume of stock exchange indexes in t -time, X_{kt} – value of regressor k in period t , ε_t – random component normally distributed $N(0,1)$.

The best fits are usually obtained with (G)ARCH(p, q) models. Significant results are obtained for the first two types: ARCH(q) and GARCH(p, q).

The basic ARCH(q) model is expressed as in the work of Engle (1982):

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2, \quad (12)$$

where h_t – conditional variance, $\varepsilon_t | I_{t-1} \sim N(0, h_t)$, I_t – the set of information available in period t , $\alpha_0 > 0$, $\alpha_i \geq 0$, $i = 1, \dots, q$ and

$$\sum_{i=1}^q \alpha_i < 1.$$

The ARCH process is the special case of a more general model called GARCH. GARCH stands for Generalized ARCH, and it adds lags in the variance to equation (2). The GARCH(p, q) is expressed as in the work of Bollerslev (1986):

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j h_{t-j}. \quad (13)$$

The following parameters should comply with the conditions to guarantee the variance will be non-negative:

$$\alpha_0 > 0, \alpha_i \geq 0, \beta_j \geq 0, i = 1, \dots, q, j = 1, \dots, p.$$

The maximum likelihood methods of parameters estimation procedure is given by:

$$\begin{aligned} \ln L = & -\frac{N}{2} \ln 2\pi - \\ & -\frac{1}{2} \sum_{t=1}^N \ln h_t(\theta) - \\ & -\frac{1}{2} \sum_{t=1}^N \frac{R_t^2}{h_t(\theta)}, \end{aligned} \quad (14)$$

where $\ln L$ – the likelihood function, N – the length of the time period, $h_t(\theta)$ – the conditional variance described by function:

$$h_t(\theta) = e^{\alpha_1 + \alpha_2 \cdot \ln \varepsilon_t}, \quad (15)$$

R_t – residuals from the regression.

Another kind of models, which could be used for identification of the relationship between analyzed variables, are vector autoregression models (VAR) described by Simms (1980):

$$y_t = \alpha_{10} + \sum_{j=1}^k \alpha_{1j} y_{t-j} + \sum_{j=1}^k \beta_{1j} x_{t-j} + \varepsilon_{1t}, \quad (16)$$

$$x_t = \alpha_{20} + \sum_{j=1}^k \alpha_{2j} x_{t-j} + \sum_{j=1}^k \beta_{2j} y_{t-j} + \varepsilon_{2t}. \quad (17)$$

The estimation was carried out using the GRETl program.

3. RESULTS

During estimation, different types of econometric models were used. Based on it, it has been established that the best results for every stock exchange index were obtained for autoregressive conditional heteroscedasticity models (GARCH). Tables 1-4 present the results of the best models' estimations.

The first model – for DAX index – indicates the negative relationship between the dependent variable (logarithm of trading volume) and dummy variable representing Mondays (calendar effect), the current return rate, and 1-day-lagged 30-days volatility. The volatility has the most substantial impact on the volume among these variables. Positive relationships were observed for the dummy variable representing Tuesdays, current, and 2-days-lagged 30-days volatility. It can be concluded that in this case, taking into account both the positive and negative impact on the dependent variable, volatility had the most significant impact on changes in the volume of trading. The best approximation was obtained for the ARCH(1) model.

The second model presented in the research is a model concerning relationships for the S&P500 index. The best approximation was obtained for the GARCH(1,1) model. Similarly, the DAX obtained negative relations between the dependent variable and Mondays and 1-day-lagged 30-days volatility, but the most substantial impact was observed for the current 30-days volatility. The other negative relation was observed for 2-days-lagged 30-days volatility. The following variables positively impact the changes in trading volume: dummy variables representing Tuesdays, Wednesdays, and Thursdays and current and 5-days-lagged 30-days volatility. Similarly, to DAX analysis, the most significant impact on trading volume was observed for the volatility.

Table 1. ARCH(1) estimation for DAX index

Source: Own calculations.

	Coefficient	St. error	z-value	p-value
Const.	0.0386635	0.00789163	4.899	< 0.0001***
Mo	-0.246699	0.0100618	-24.52	< 0.0001***
Tu	0.0946003	0.00990589	9.550	< 0.0001***
R_t	-1.52320	0.271436	-5.612	< 0.0001***
V30	83.7347	6.82883	12.26	< 0.0001***
$V30_{t-1}$	-144.898	10.7491	-13.48	< 0.0001***
$V30_{t-2}$	60.9593	7.18314	8.486	< 0.0001***
(G)ARCH model's parameters				
alpha(0)	0.0552942	0.00158859	34.81	< 0.0001***
alpha(1)	0.312818	0.0249275	12.55	< 0.0001***
Estimation parameters				
Mean	-0.000188	St. deviation	0.316795	
Likelihood logarithm	-484.3898	AIC	988.7797	
SIC	1052.651	HQC	1011.314	

Table 2. GARCH(1,1) estimation for S&P500 index

Source: Own calculations.

	Coefficient	St. error	z-value	p-value
Const.	-0.0166787	0.00953421	-1.749	0.0802*
Mo	-0.112516	0.0112045	-10.04	< 0.0001***
Tu	0.0389215	0.0109245	3.563	0.0004***
We	0.0993788	0.0108837	9.131	< 0.0001***
Th	0.0665704	0.0112109	5.938	< 0.0001***
V30	37.6172	6.57614	5.720	< 0.0001***
V30 _{t-1}	-25.9298	9.95217	-2.605	0.0092***
V30 _{t-2}	-32.2613	7.87566	-4.096	< 0.0001***
V30 _{t-5}	20.1806	3.30803	6.100	< 0.0001***
(G)ARCH model's parameters				
alpha(0)	0.0362913	0.00463460	7.831	< 0.0001***
alpha(1)	0.253623	0.0227647	11.14	< 0.0001***
beta(1)	0.281107	0.0691380	4.066	< 0.0001***
Estimation parameters				
Mean	0.000890	St. deviation		0.290548
Likelihood logarithm	-493.4239	AIC		1012.848
SIC	1098.586	HQC		1042.779

The third presented model concerns the influence of the most statistically significant independent variables (taken into consideration) on changes in trading volume for the NIKKEI index. Negative regression parameters were observed for three variables: dummy variables representing Mondays and Thursdays and 1-day-lagged 30-days volatility. Positive regression parameters were observed for current, 2-days-lagged, and 4-days-lagged 30-days volatility. The 1-day-lagged volatility results most strongly on the trading volume diversity of the NIKKEI

index. The best approximation was obtained for the ARCH(1) model.

The last model presented is for the FTSE 100 index from the London Stock Exchange. The best approximation for the estimated model was obtained for GARCH(1,1). Negative-sign parameters are obtained for dummy variable representing Mondays and 1-day-lagged 30-days volatility. Current and 3-days-lagged volatility positively results in a dynamic in trading volume. Also, in that case, the strongest relations were obtained for volatility.

Table 3. ARCH(1) estimation for NIKKEI 225 index

Source: Own calculations.

	Coefficient	St. error	z-value	p-value
Const.	0.0400115	0.00621497	6.438	< 0.0001***
Mo	-0.155787	0.00767460	-20.30	< 0.0001***
Th	-0.0238561	0.00735387	-3.244	0.0012***
V30	43.2920	4.31765	10.03	< 0.0001***
V30_1	-68.5557	6.89119	-9.948	< 0.0001***
V30_2	11.1330	5.82317	1.912	0.0559*
V30_4	13.7791	2.74029	5.028	< 0.0001***
(G)ARCH model's parameters				
alpha(0)	0.0277887	0.000825436	33.67	< 0.0001***
alpha(1)	0.190031	0.0229957	8.264	< 0.0001***
Estimation parameters				
Mean	0.000091	St. deviation		0.198605
Likelihood logarithm	1152.113	AIC		-2284.226
SIC	-2221.154	HQC		-2261.884

Table 4. GARCH(1,1) estimation for FTSE 100 index

Source: Own calculations.

	Coefficient	St. deviation	z-value	p-value
Const.	0.0887225	0.0112101	7.915	< 0.0001***
Mo	-0.248021	0.0134296	-18.47	< 0.0001***
V30	71.0842	10.9879	6.469	< 0.0001***
V30_1	-119.258	14.4610	-8.247	< 0.0001***
V30_3	46.2885	7.63560	6.062	< 0.0001***
(G)ARCH model's parameters				
alpha(0)	0.0638535	0.00396779	16.09	< 0.0001***
alpha(1)	0.452913	0.0510093	8.879	< 0.0001***
beta(1)	0.378281	0.0325288	11.63	< 0.0001***
Estimation parameters				
Mean	-0.000039	St. deviation		0.498432
Likelihood logarithm	-2010.144	AIC		4038.288
SIC	4095.725	HQC		4058.557

4. DISCUSSION

The results of the estimation of econometric models for the DAX trading volumes were presented in Table 1. The best approximation was obtained for the ARCH(1) model (the highest value of maximum likelihood function with statistically significant parameters). The first fact is the occurrence of the Monday effect (already known in the literature). Every Monday, the logarithm of trading volume significantly decreases and, every Tuesday, increases. However, the most significant changes in the index trading volume's logarithms are caused by changes in 1-day-lagged 30-days volatility. Much smaller reactions of trading volume were obtained for 30-days volatility without lags and 2-days-lagged 30-days volatility. There is also a significant negative relationship between the index's rates of return and trading volume.

The model describing relations for the S&P500 index was presented in Table 2. The best approximation for the econometric function was obtained for the GARCH(1,1) model in this case. The negative impact of the Monday effect was also observed for Standard and Poor's 500, but there were also relationships between the trading volume and Tuesdays, Wednesdays, and Thursdays (positive in all these cases). Similarly to the previous table, the highest impacts are caused by

30-days-volatility. The highest absolute value of parameter was obtained for volatility without any lags, and it was positive. The negative values of econometric models' parameters were obtained for 1- and 2-days-lagged volatility. The parameter for 5-days-lagged volatility was also positive.

The estimation of econometric models for the NIKKEI 225 index allows for the determination of some regularities (presented in Table 3). First, the best approximation was obtained for the ARCH (1) model. Second, the Monday effect exists on the Tokyo Stock Exchange. Third, the highest absolute value of parameter was obtained for 1-day-lagged 30-days volatility, and it was negative. The third negative parameter was obtained for the dummy variable representing Thursdays. Positive significant parameters were obtained for the 30-days volatility without lags and 2- and 4-days-lagged volatility.

Table 4 presents the results for the FTSE 100 index. The best results were obtained for the GARCH (1,1) model, and the following variables: Mondays (dummy variable), 30-days volatility (current, 1- and 3-days-lagged). The value of the parameter for Mondays was negative, as in other cases. The highest absolute value of the parameter was obtained for 1-day-lagged 30-days volatility, and it was negative. The parameters of the other two variables were positive.

CONCLUSION

As it has been assumed, changes in trading volume illustrate investors' emotions, and the volatility reflects the trading activity of stock exchange investors. Based on this research, it is possible to conclude that the volatility is the significant regressor of econometric models describing trading volume for analyzed stock exchanges having a substantial impact on this dependent variable. This hypothesis has been verified positively. So, it can be said that volatility could measure the emotions of stock exchange investors.

The analysis included three kinds of time-windows for the volatility of 30, 90, and 180 days and the best results have been obtained for the shortest period. An exciting result concerns time-lagged volatility – in every analyzed case, it indicated a negative relation for t-1 lag and positive relation for current volatility, but it was not stable for the other lags.

Additionally, it turned out that the one-day-in-week effect biased every analyzed stock exchange index, and every Monday, trading volume negatively deviates from the trend line.

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