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# **MOY Effects in returns and in volatilities of the Romanian Capital Market**

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**Abstract:** This paper explores Month-of-the-year effects in returns and in volatilities of the Bucharest Stock Exchange. Our investigation covers two periods: the first one, from January 2000 to January 2006, corresponds to the last stage of Romania's transition to a capitalist system, while the second one, from January 2007 to August 2013, is marked by the adhesion to European Union and by the effects of the global crisis. We use GARCH models to identify the monthly seasonality in returns and in volatilities. The results indicate significant changes of this calendar anomaly from the first to the second period.

**Keywords:** Monthly Seasonality, Romanian Capital Market, GARCH

**JEL Classification:** G02, G10, G14, G19

## **Introduction**

The Month-of-the-year (MOY) effect, which is one of the best known calendar anomalies, consists in significant differences between the month stock prices returns. The first investigations about this seasonality found that usually in January the returns were much higher than in December. This calendar anomaly was explained by several hypotheses such as: Window Dressing Hypothesis, Tax Loss Selling Hypothesis or Differential Information Hypothesis. Later researches revealed MOY effects associated with other months. The growing importance of the volatility in the investment decisions stimulated the use of General AutoRegressive Conditional

Heteroskedasticity (GARCH) models in analysis of stock market seasonality (Engle, 1982; Bollerslev, 1986).

The persistence in time of the calendar anomalies is one of the most controversial subjects of the financial literature. The exploitation of stock market seasonality is difficult when it is affected by changes (Dimson & Marsh, 1999; Marquering et al., 2006; Siriopoulos & Giannopoulos, 2006). The change in time of the calendar anomalies weakens the use of them as arguments for the behavioral finance theory against Fama (1970) Efficient Markets Hypothesis.

In this paper we investigate the presence of the MOY Effects on the Bucharest Stock Exchange (BSE) from January 2000 to August 2013. We perform our analysis for two periods of time. The first of them, from January 2000 to December 2006, which covers the last stage of Romania's transition to a capitalist system, could be consider as relatively quiet. The second period of time is from January 2007 to August 2013, when the effects of Romania's adhesion to European Union and the impact of the global crisis induced significant turbulences on BSE. In this investigation we employ GARCH models to reveal the seasonality not only for the indexes returns but also for their volatility.

The rest of this paper is organized as it follows. The second part describes the methodology used to investigate MOY effects, the third part presents the results and the fourth part concludes.

## **2. DATA AND METHODOLOGY**

In this investigation about the presence of MOY Effects we employ daily closing values of five important indexes of BSE: BET, BET-C, BET-FI, BET-XT and BET-NG from January 2000 to August 2013. Their composition and the periods of time they cover are presented in the Table 1. We use two sub-samples of data:

- the first sub-sample, with values of only three indexes (BET, BET C and BET FI) from January 2000 to December 2006, corresponding to a relative quiet period;
- the second sub-sample, with values of all the indexes, from January 2007 to August 2013, corresponding to a turbulent period.

**Table 1** - Compositions and sub-samples of the BSE indexes

<b>Index</b>	<b>Composition</b>	<b>First sub-sample</b>	<b>Second sub-sample</b>
BET	Calculated based on the shares prices of most liquid 10 companies listed on the BSE regulated market	January 2000 - December 2006	January 2007 – August 2013
BET-C	Calculated based on the shares prices of the big companies listed on BSE, excepting the investment funds (SIFs)	January 2000 - December 2006	January 2007 – August 2013
BET-FI	Calculated based on the shares prices of the five investment funds (SIFs)	November 2000 - December 2006	January 2007 – August 2013
BET-XT	Calculated based on the shares prices of the most liquid 25 shares traded on BSE, including SIFs	x	January 2007 – August 2013
BET-NG	Calculated based on the shares prices of the shares of companies which have the main business activity located in the energy sector and the related utilities	x	January 2007 – August 2013

For all the five indexes we calculate logarithmic returns ( $r_{i,t}$ ) as:

$$r_t = [\ln(P_t) - \ln(P_{t-1})] * 100 \quad (1)$$

where  $P_t$  and  $P_{t-1}$  are the closing prices of an index on the days  $t$  and  $t-1$ , respectively.

In order to avoid the spurious regressions on GARCH models we investigate, for each index, the stationarity of returns by employing the Augmented Dickey – Fuller (ADF) unit root tests (Dickey and Fuller, 1979). In these tests we use intercept as deterministic term, choosing the numbers of lags based on the Akaike Information Criterion (Akaike, 1973). We investigate also the autocorrelation and the heteroscedasticity of returns by employing ARMA (p, q) models, in which the values of p and q are determined by Box-Jenkins methodology (Box et al., 1994). We run the Ljung - Box test Q and the Engle Lagrange Multiplier (LM) test for ARCH effects on the residuals of ARMA regressions we (Ljung & Box, 1978; Engle, 1982).

We also use dummy variables ( $D_j$ ) that correspond to each month of the year. A variable  $D_j$  takes the value one for the month  $j$  and zero otherwise.

In this investigation we employ three variants of GARCH models: the classic one, GJR GARCH and EGARCH.

The GARCH model is described by two equations: the conditional mean and the conditional variance. The first equation allows us to identify the MOY effects on the returns ( $r_t$ ):

$$r_t = \sum_{j=1}^{12} \mu_j * D_{j,t} + \sum_{k=1}^n (\xi_k * r_{t-k}) + \varepsilon_t \quad (2)$$

where:

- $\mu_j$  is a coefficient associated to the dummy variable  $D_j$ , reflecting MOY effect for the month  $j$ ;

- $\xi_k$  is a coefficient of the  $k$ -order lagged returns;

- $n$  represents the number of lagged returns, calculated by the Akaike Final Prediction Error Criterion (Akaike, 1969);

- $\varepsilon_t$  is the error term.

The second equation expresses the seasonality of the conditional variance of the returns ( $\sigma_t^2$ ):

$$\sigma_t^2 = \omega + \sum_{j=1}^{12} v_j * D_{j,t} + \sum_{k=1}^q \alpha_k * \varepsilon_{t-k}^2 + \sum_{l=1}^p (\beta_l * \sigma_{t-l}^2) \quad (3)$$

where:

- $\omega$  is a constant term;
- $v_j$  is a coefficient associated to the dummy variable  $D_j$ , reflecting MOY effect on the stocks volatility for the month  $j$ ;
- $\alpha_k$  ( $k = 1, 2, \dots, q$ ) are the coefficients associated to the squared values of the lagged values of error term from the conditional mean equation;
- $q$  is the number of lagged values of the error term, calculated by the Akaike Information Criterion (Akaike, 1973);
- $\beta_l$  ( $l = 1, 2, \dots, p$ ) are coefficients associated to the lagged values of the conditional variance;
- $p$  is the number of lagged values of conditional variance, calculated also by the Akaike Information Criterion.

The Glosten et al. (1993) GJR GARCH model employed in our investigation allows us to capture the asymmetrical reactions of stocks volatility on good and bad news. It used the same conditional mean equation as the classic GARCH model to identify MOY effects on the returns. The monthly seasonality of conditional variance of the returns is revealed by the equation:

$$\sigma_t^2 = \omega + \sum_{j=1}^{12} v_j * D_{j,t} + \sum_{k=1}^q [\alpha_k * \varepsilon_{t-k}^2 + \gamma_k * \varepsilon_{t-k}^2 * I(\varepsilon_{t-k} < 0)] + \sum_{l=1}^p (\beta_l * \sigma_{t-l}^2) \quad (3)$$

where:

- $I(\varepsilon_{t-k} < 0)$  is a dummy variable, taking the value 1 if the  $k$ -lagged error term is strict negative and value zero otherwise;
- $\gamma_k$  is the coefficient associated to the variable  $I(\varepsilon_{t-k} < 0)$ , expressing the asymmetrical responses of the volatility to the good and bad news.

Nelson (1991) EGARCH model could also identify the asymmetric reactions of stock markets to good and bad news. The seasonality of the returns is revealed by the conditional mean equation of the classical GARCH model. The MOY effects on volatility could be analyzed by the conditional variance equation:

$$\ln(\sigma_t^2) = \omega + \sum_{j=1}^{12} \nu_j * D_{j,t} + \sum_{r=1}^p \beta_r * \ln(\sigma_{t-r}^2) + \sum_{k=1}^p \left[ \gamma_k * \frac{\varepsilon_{t-k}}{\sqrt{\sigma_{t-k}^2}} + \alpha_k * \left( \frac{\varepsilon_{t-k}}{\sqrt{\sigma_{t-k}^2}} - \sqrt{\frac{2}{\pi}} \right) \right] \quad (4)$$

which could be transformed in:

$$\ln(\sigma_t^2) = \omega + \sum_{j=1}^{12} \nu_j * D_{j,t} + \sum_{r=1}^p \beta_r * \ln(\sigma_{t-r}^2) + \sum_{k=1}^p [\gamma_k * \varepsilon_{t-k} + \alpha_k * |\varepsilon_{t-k}|] \quad (5)$$

$$\text{where } \omega = \omega - \sqrt{\frac{2}{\pi}} * \sum_{k=1}^p \alpha_k \quad (6)$$

For all the returns, we investigate the presence of the ARCH effects on the residuals of GARCH equations by employing Lagrange Multiplier (LM) tests. If the residuals display no ARCH effects we shall consider the model as valid. We choose between the valid GARCH models using as criteria the significance of the specific GARCH terms.

### 3. EMPIRICAL RESULTS

The Table 2 reports the results of ADF tests. We found that returns of indexes are stationary for both sub-samples.

The results of Ljung - Box Q and ARCH LM tests are presented in the Table 3. We identify, for all the time series, the presence of autocorrelation and the heteroscedasticity.

For the first sub-sample the classic GARCH (1,1) is chosen for all three returns. The results of the conditional mean equation indicate some significant MOY effects. For BET we found positive January, July and October effects. In the case of BET C we identify positive January, September, October and November effects. For BET FI we found positive January, April, June, July, August, October and December effects (Table 4).

**Table 2** - Results of ADF tests for the returns

Index	First sub-sample		Second sub-sample	
	Number of lags	Test statistics	Number of lags	Test statistics
BET	24	-8.4191***	19	-7.2387***
BET C	19	-8.1541***	21	-7.1229***
BET FI	16	-7.8025***	19	-8.0522***
BET XT	x	x	16	-7.5109***
BET NG	x	x	15	-11.488***

**Note:** \*\*\*, \*\*, \* mean significant at 0.01, 0.05 and 0.1 levels, respectively.

**Table 3** - Results of Ljung-Box Q and ARCH LM tests

Index	First sub-sample		Second sub-sample	
	Ljung-Box Q Tests	ARCH LM Tests	Ljung-Box Q Tests	ARCH LM Tests
BET	11.054*	219.30***	10.338*	256.04***
BET C	7.649*	171.07***	8.574**	286.06***
BET FI	15.234***	117.14***	9.148**	369.02***
BET XT	x	x	7.494*	316.14***
BET NG	x	x	8.331**	508.90***

**Note:** \*\*\*, \*\*, \* mean significant at 0.01, 0.05, and 0.1 levels, respectively.

**Table 4** - Results of conditional mean equation for the first sub-sample



Index	BET	BET C	BET FI
$\mu_1$	0.452951 (2.703) [0.167557]***	0.461799 (0.136882) [3.374]***	0.457248 (0.173577) [2.634]***
$\mu_2$	0.160385 (0.126418) [1.269]	0.118242 (0.102454) [1.154]	-0.205280 (0.155177) [-1.323]
$\mu_3$	0.0144001 (0.103587) [0.1390]	-0.043152 (0.0850609) [-0.5073]	-0.051467 (0.115892) [-0.4441]
$\mu_4$	0.0792282 (0.111512) [0.7105]	0.0927248 (0.0937636) [0.9889]	0.452461 (0.169973) [2.662]***
$\mu_5$	0.0355179 (0.0971282) [0.3657]	0.0235374 (0.0959423) [0.2453]	0.0387500 (0.164786) [0.2352]
$\mu_6$	0.123331 (0.0842628) [1.464]	0.0789928 (0.0686863) [1.150]	0.299393 (0.158810) [1.885]*
$\mu_7$	0.166873 (0.0878889) [1.89]*	0.102143 (0.0711993) [1.435]	0.289163 (0.134417) [2.151]**
$\mu_8$	0.0504887 (0.0748430) [0.6746]	0.0352112 (0.0617542) [0.5702]	0.217641 (0.120847) [1.801]*
$\mu_9$	0.0949289	0.150996	0.0346327

	(0.0776399) [1.223]	(0.0755820) [1.998]**	(0.139023) [0.2491]
$\mu_{10}$	0.232151 (0.0744041) [3.120]***	0.170384 (0.0605245) [2.815]***	0.356428 (0.127565) [2.794]***
$\mu_{11}$	0.107888 (0.0732710) [1.472]	0.119250 (0.0667612) [1.786]*	0.169056 (0.115940) [1.458]
$\mu_{12}$	0.188939 (0.127402) [1.483]	0.103402 (0.106122) [0.9744]	0.335604 (0.172674) [1.944]*
First order lagged returns	0.126528 (0.0265367) [4.768]***	0.144053 (0.0275074) [5.237]***	x

**Notes:** Standard errors in round brackets; z-statistics in square brackets;

\*\*\*, \*\*, \* mean significant at 0.01, 0.05, and 0.1 levels, respectively.

The Table 5 reports the results of conditional variance equation for the first sub-sample. For BET index we identify significant coefficients corresponding to all the months excepting February, March, April and December. Instead, we found no seasonality for BET C index. For the third index, BET FI, significant coefficients for all the dummy variables resulted.

**Table 5 - Results of conditional variance equation for the first sub-sample**

Index	BET GARCH (1,1)	BET C GARCH (1,1)	BET FI GARCH (1,1)
$\omega$	1.75082	1.53307	2.03520

	(0.971536) [1.802]*	(1.03516) [1.481]	(1.27846) [1.592]
v <sub>1</sub>	1.34537 (0.704475) [-1.910]*	-0.86664 (0.829589) [-1.045]	-2.16113 (1.26408) [-1.710]*
v <sub>2</sub>	-1.49527 (0.909525) [-1.644]	-1.17769 (0.949005) [-1.241]	-2.10474 (1.26513) [-1.664]*
v <sub>3</sub>	-1.43412 (0.898625) [-1.596]	-1.09059 (0.981278) [-1.111]	-2.21467 (1.27695) [-1.734]*
v <sub>4</sub>	-1.40670 (0.888539) [-1.583]	-1.13061 (0.975181) [-1.159]	-2.14194 (1.27209) [-1.684]*
v <sub>5</sub>	-1.47367 (0.894949) [-1.647]*	-1.14792 (0.98103) [-1.170]	-2.19324 (1.27385) [-1.722]*
v <sub>6</sub>	-1.59562 (0.935265) [-1.706]*	-1.35219 (1.00659) [-1.343]	-2.14761 (1.27367) [-1.686]*
v <sub>7</sub>	-1.59053 (0.920186) [-1.728]*	-1.32275 (0.996325) [-1.328]	-2.20427 (1.27455) [-1.729]*
v <sub>8</sub>	-1.61745 (0.934648) [-1.731]*	-1.33802 (1.00332) [-1.334]	-2.20293 (1.27547) [-1.727]*
v <sub>9</sub>	-1.65259	-1.33658	-2.21501

	(0.933760) [-1.770]*	(0.996974) [-1.341]	(1.27777) [-1.733]*
V <sub>10</sub>	-1.59747 (0.928542) [-1.720]*	-1.34805 (1.00285) [-1.344]	-2.18254 (1.27433) [-1.713]*
V <sub>11</sub>	-1.60651 (0.934087) [-1.720]*	-1.34612 (1.00567) [-1.339]	-2.18853 (1.27557) [-1.716]*
V <sub>12</sub>	-1.38193 (0.930016) [-1.486]	-1.22736 (0.999783) [-1.228]	-2.09954 (1.27515) [-1.647]*
alpha	0.212515 (0.0647837) [3.280]***	0.278096 (0.0710268) [3.915]***	0.367473 (0.0613343) [5.991]***
beta	0.699172 (0.114115) [6.127]***	0.557897 (0.151551) [3.681]***	0.919913 (0.0243999) [37.701]***
ARCH LM tests for the residuals of GARCH models	6.4821	15.8241	2.2068

**Notes:** Standard errors in round brackets; z-statistics in square brackets;

\*\*\*, \*\*, \* mean significant at 0.01, 0.05, and 0.1 levels, respectively.

For the second sub-sample we chose the classical GARCH (1,1) model for BET C index, GJR GARCH (1,1) model for BET FI index and EGARCH (1,1) model

for the rest of three indexes. The results of conditional mean equations are presented in the Table 6. For BET index we find significant coefficients for January (positive) and November (negative). We identify also two MOY effects on BET C returns: February (positive) and November (negative). BET FI index displays no seasonality of the returns. For the returns of BET XT index the results revealed one positive MOY effect (for February) and two negative ones (May and July). We identify only a February positive effect for BET NG index.

**Table 6** - Results of conditional mean equations for the second sub-sample

<b>Index</b>	<b>BET</b>	<b>BET C</b>	<b>BET FI</b>	<b>BET XT</b>	<b>BET NG</b>
$\mu_1$	0.16738 (0.09147) [1.830]*	0.15914 (0.09824) [1.620]	0.05087 (0.23076) [0.221]	0.12471 (0.10587) [1.178]	0.11510 (0.10271) [1.121]
$\mu_2$	0.12529 (0.09052) [1.384]	0.16992 (0.08611) [1.973]**	0.05961 (0.09327) [0.6391]	0.14386 (0.08602) [1.672]*	0.21322 (0.10797) [1.975]**
$\mu_3$	0.14457 (0.09184) [1.574]	0.09364 (0.07598) [1.232]	-0.02898 (0.15755) [-0.1840]	0.11665 (0.14399) [0.8101]	0.03357 (0.09747) [0.3444]
$\mu_4$	-0.07575 (0.09352) [-0.8100]	-0.04565 (0.08335) [-0.5477]	-0.14749 (0.11287) [-1.307]	-0.12513 (0.10060) [-1.244]	0.00541 (0.10189) [0.05314]
$\mu_5$	-0.11388 (0.10123) [-1.125]	-0.10703 (0.08971) [-1.193]	-0.21953 (0.15428) [-1.423]	-0.15380 (0.0416) [-2.506]***	-0.14482 (0.11322) [-1.279]
$\mu_6$	-0.06138 (0.09000) [-0.6820]	-0.07495 (0.10569) [-0.7091]	-0.10326 (0.17349) [-0.5952]	-0.17082 (0.0312) [-2.304]***	-0.15713 (0.11179) [-1.405]
$\mu_7$	0.12899 (0.09582)	0.08706 (0.07617)	-0.06324 (0.12825)	0.08814 (0.08473)	0.08399 (0.09973)

	[1.346]	[1.143]	[-0.4932]	[1.040]	[0.8422]
$\mu_8$	0.02581 (0.09033) [0.2858]	0.06347 (0.08635) [0.7350]	0.13990 (0.13329) [1.050]	0.05138 (0.15511) [0.3313]	0.04590 (0.09182) [0.4999]
$\mu_9$	-0.07729 (0.10260) [-0.7533]	-0.09230 (0.09611) [-0.9603]	0.11679 (0.15949) [0.7323]	-0.05731 (0.11875) [-0.4826]	-0.07586 (0.11154) [-0.6801]
$\mu_{10}$	0.01886 (0.10111) [0.1865]	0.03581 (0.07076) [0.5061]	0.05732 (0.14962) [0.3831]	-0.00556 (0.08508) [-0.06545]	-0.06902 (0.12093) [-0.5708]
$\mu_{11}$	-0.15721 (0.07217) [-2.178]**	-0.14862 (0.06842) [-2.172]**	-0.19846 (0.13340) [-1.488]	-0.16958 (0.08565) [-1.980]	-0.114451 (0.07380) [-1.551]
$\mu_{12}$	0.06704 (0.09897) [0.6774]	0.09340 (0.07383) [1.265]	0.21718 (0.14883) [1.45]	0.15910 (0.11343) [1.403]	0.12805 (0.09835) [1.302]
First order lagged returns	0.06515 (0.02525) [2.580]***	0.07353 (0.02638) [2.787]***	x	x	x

**Notes:** Standard errors in round brackets; z-statistics in square brackets;

\*\*\*, \*\*, \* mean significant at 0.01, 0.05, and 0.1 levels, respectively.

For the second sub-sample the results of conditional variance equation revealed no MOY effects on volatility (Table 7).

**Table 7 - Results of conditional variance equation for the second sub-sample**

Index	BET EGARCH	BET C GARCH (1,1)	BET FI GJR	BET XT EGARCH	BET NG EGARCH
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	(1,1)		GARCH (1,1)	(1,1)	(1,1)
$\omega$	-0.39867 (0.77829) [-0.5122]	-0.37303 (0.33260) [-1.122]	-2.84474 (3.52978) [-0.8059]	-1.05234 (2.23877) [-0.4701]	0.30083 (0.73447) [0.4096]
$v_1$	0.18725 (0.77799) [0.2407]	0.42744 (0.33697) [1.268]	2.79178 (3.52344) [0.7923]	0.85652 (2.20135) [0.3891]	-0.45805 (0.73472) [-0.6234]
$v_2$	0.19858 (0.78397) [0.2533]	0.41393 (0.33539) [1.234]	2.87933 (3.52765) [0.8162]	0.87254 (2.20235) [0.3962]	-0.47133 (0.74002) [-0.6369]
$v_3$	0.18105 (0.78230) [0.2314]	0.41078 (0.33921) [1.211]	2.83205 (3.53013) [0.8023]	0.87433 (2.21011) [0.3956]	-0.48785 (0.73904) [-0.6601]
$v_4$	0.19779 (0.77767) [0.2543]	0.40123 (0.33490) [1.198]	2.90039 (3.52931) [0.8218]	0.87941 (2.19519) [0.4006]	-0.44556 (0.73393) [-0.6071]
$v_5$	0.21657 (0.77936) [0.2779]	0.42784 (0.33561) [1.275]	2.90619 (3.52922) [0.8235]	0.89305 (2.20540) [0.4049]	-0.44812 (0.73618) [-0.6087]
$v_6$	0.18156 (0.77824) [0.2333]	0.41930 (0.33763) [1.242]	2.85809 (3.52452) [0.8109]	0.86557 (2.20478) [0.3926]	-0.48995 (0.73480) [-0.6668]
$v_7$	0.21877 (0.77862) [0.2810]	0.41740 (0.33707) [1.238]	2.83973 (3.53121) [0.8042]	0.89009 (2.19729) [0.4051]	-0.46302 (0.73544) [-0.6296]
$v_8$	0.15439 (0.77871) [0.1983]	0.37833 (0.33436) [1.132]	2.87882 (3.52221) [0.8173]	0.84165 (2.20011) [0.3825]	-0.47521 (0.73556) [-0.6461]
$v_9$	0.22856 (0.77892)	0.44131 (0.33826)	2.86654 (3.53201)	0.90875 (2.20433)	-0.45960 (0.73572)

	[0.2934]	[1.305]	[0.8116]	[0.4123]	[-0.6247]
v <sub>10</sub>	0.18567 (0.77881) [0.2384]	0.37074 (0.33353) [1.112]	2.83768 (3.52523) [0.8050]	0.85909 (2.19912) [0.3907]	-0.46196 (0.73542) [-0.6282]
v <sub>11</sub>	0.15413 (0.77871) [0.1979]	0.39573 (0.33502) [1.181]	2.87451 (3.52628) [0.8152]	0.85439 (2.20300) [0.3878]	-0.52249 (0.73592) [-0.7100]
v <sub>12</sub>	0.22954 (0.77816) [0.2950]	0.41162 (0.33405) [1.232]	2.91097 (3.53908) [0.8225]	0.91379 (2.19525) [0.4163]	-0.43397 (0.73524) [-0.5902]
alpha	0.29720 (0.03526) [8.428]***	0.14867 (0.03688) [4.031]***	0.10899 (0.03076) [3.542]***	0.25404 (0.08256) [3.077]***	0.24368 (0.02954) [8.249]***
gamma	-0.04350 (0.02074) [-2.097]**	x	0.13987 (0.05271) [2.653]***	-0.03754 (0.01718) [-2.185]**	-0.04751 (0.01773) [-2.678]***
beta	0.97400 (0.00711) [136.8]***	0.84550 (0.03635) [23.26]***	0.89581 (0.02795) [32.041]***	0.98292 (0.01126) [87.280]***	0.97900 (0.00644) [151.9]***
ARCH LM tests for the residuals of GARCH models	40.0214	40.1061	4.2815	8.2180	7.9853

**Notes:** Standard errors in round brackets; z-statistics in square brackets;

\*\*\*, \*\*, \* mean significant at 0.01, 0.05, and 0.1 levels, respectively.

## Conclusions



In this paper we investigated the presence of MOY effects on returns and volatility of BSE during two periods of time: the first one, from 2000 to 2006, which could be considered as relatively quiet, while the second one, from 2006 to 2013, was marked by turbulences. We found significant changes of MOY effects from the first to the second period of time.

From 2000 to 2006 we identified only positive MOY effects on returns. We found significant differences among the seasonality of three returns. The conditional variance equations revealed also, for two of the three indexes, significant monthly seasonality of volatility. The MOY effects are much more consistent for BET FI index than to the other two indexes. We could explain these differences by the fact that BET FI index is calculated based on the share prices of investment funds, which are bought mainly for speculative purposes.

From 2007 to 2013 the investigation revealed both positive and negative MOY effects on returns. Only January effect of BET remained from the first to the second period. BET FI displayed no monthly seasonality of returns. The MOY effects on volatility disappeared from the quiet to the turbulent times. This evolution could be viewed as a confirmation of Calendar anomalies Murphy Law, proposed by Dimson and Marsh (1999). Another explanation could involve the passage from the quiet to the turbulent times. In general, the regularities of investors' behaviors are favored by the quiet times but inhibited by the turbulent ones.

This investigation could be extended to other emerging markets.

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