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Calendar Anomalies in the Russian Stock Market

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CALENDAR ANOMALIES

IN THE RUSSIAN STOCK MARKET

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Abstract

This paper investigates whether or not calendar anomalies (such as the January, day-of-the-week and turn-of-the-month effects) characterise the Russian stock market, which could be interpreted as evidence against market efficiency. Specifically, OLS, GARCH, EGARCH AND TGARCH models are estimated using daily data for the MICEX market index over the period 22/09/1997-14/04-2016. The empirical results show the importance of taking into account transactions costs (proxied by the bid-ask spreads): once these are incorporated into the analysis calendar anomalies disappear, and therefore there is no evidence of exploitable profit opportunities based on them that would be inconsistent with market efficiency.

Keywords: calendar effects, Russian stock market, transaction costs

JEL classification: G12, C22

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1 Introduction

There is a large literature testing for the presence of calendar anomalies (such as the "day-of-the-week", “day-of-the-month” and "month-of-the-year” effects) in asset returns. Evidence of this type of anomalies has been seen as inconsistent with the efficient market hypothesis (EMH – see Fama, 1965, 1970 and Samuelson, 1965), since it would imply that trading strategies exploiting them can generate abnormal profits. However, a serious limitation of many studies on this topic is that they neglect transaction costs: broker commissions, spreads, payments and fees connected with the trading process may significantly affect the behaviour of asset returns and calendar anomalies might disappear once they are taken into account, the implication being that in fact there are no exploitable profit opportunities based on them that would negate market efficiency.

The present study examines calendar anomalies in the Russian stock market incorporating transaction costs in the estimated models in order to address the aforementioned criticism. Specifically, four models are estimated: OLS, GARCH, TGARCH, EGARCH.

The structure of the paper is the following: Section 2 reviews briefly the literature on calendar anomalies; Section 3 describes the data and outlines the methodology; Section 4 presents the empirical findings; Section 5 offers some concluding remarks.

2 Literature Review

The existence of a January effect had already been highlighted by Wachel (1942) for the period 1928-1940. Subsequent studies by Rozeff and Kinney (1976) and Lakonishok and Smith (1988) used much longer series to avoid the problems of data snooping, noise and selection bias, and found evidence of various calendar anomalies, namely January, day-of-the-week and turn-of-the-month effects. Keim (1983) and Thaler (1987) reported that the January effect characterises mainly shares of small companies, whilst Kohers and Kohli (1991) concluded that it is also typical of shares of large companies. Cross (1973) was one of the first to identify a day-of-the-week effect. Gibbons and Hess (1981) found the lowest returns were on Mondays, and the highest on Fridays. Mehdian and Perry (2001) showed a decline of this anomaly over time.

Most existing studies, such as the ones mentioned above, concern the US stock market. Only a few focus on emerging markets. For instance, Ho (1990) found a January effect in 7 out of 10 Asia-Pacific countries; Darrat (2011) analysed an extensive dataset including 34 countries and reported a January effect in all except three of them (Denmark, Ireland, Jordan); Yalcin and Yucel (2003) analysed 24 emerging markets and found a day-of the-week effect in market returns for 11 countries and in market volatility in 15 countries; Compton et al. (2013) focused on Russia and discovered various anomalies (January, day-of-the-week and turn-of-the month effect) in the MICEX index daily returns.

Transaction costs were first taken into account by Gregoriou et al. (2004), who estimated an OLS regression as well as a GARCH (1,1) model and concluded that calendar anomalies (specifically, the day-of-the-week effect) disappear when returns are adjusted using transaction costs. More recently, Caporale et al. (2015) reached the same conclusion in the case of the Ukrainian stock market using a trading robot approach.

Wachel (1942) discussed the main possible reasons for the existence of a January effect. The first is tax-loss selling: companies sell some securities before the end of the financial year to report capital losses and reduce taxable income, which pushes prices down at the end of the year; however, in January, when this pressure is over, equities rise back to their equilibrium prices, generating higher returns. The second is additional demand for cash around Christmas. The third is the anticipated improvement in the business environment in spring, and the fourth is the general positive mood around the time the new year starts. Keim (1983) also mentioned the tax-loss selling explanation. However, Gultekin and Gultekin (1983) argued that this cannot apply to all countries: for example, in Japan there is a January effect despite the absence of capital gain taxes, and in Canada this can be found even before the introduction of the capital gain tax in 1972. Another possible explanation is window dressing (see Sharpe, 1999): professional fund managers sell badly performing stocks at the end of the year in order not to include them into their annual reports.

Ritter (1988) noticed that investors make gains from selling stocks at the end of the year and then wait till January to reinvest. Schallheim and Kato (1985) argued that in Japan the January effect can be explained by bonus payments paid to employees in December that are available for investment in January and push prices up in that month; they also suggested that positive news in end-of-the-year financial reports could at least partially account for the January effect.

Damodaran (1989) argued that the main reason for the weekend effect (low returns on Mondays and high returns of Fridays) is the arrival of negative news at the beginning of the week. However, Condoyanmi (1987) and Dubois and Louvet (1996) found that in other markets such as France, Turkey, Japan, Singapore, Australia the highest negative returns appear on Tuesdays; this may be explained by the fact that these markets are influenced by American negative news with a one-day lag. Keef and McGuinness (2001) suggested that the settlement procedure could be the explanation for negative returns on Mondays (see also Kumari and

Mahendra, 2006); however, these might differ across countries. Rystrom and Benson (1989) argued investors are irrational and their sentiment depends on the day of the week, which might be the explanation for the day-of-the week effect. Finally Pettengill (2003) claimed that investors behave differently on Mondays because of scare trading, with informed investors shorting because of negative news from the weekend.

3 Data and Methodology

3.1 Data

The series analysed is the ruble-denominated, capitalisation-weighted MICEX market index. The sample includes 4633 observations on (close-to-close) daily returns and covers the period from 22/09/1997 (when this index was created) till 14/04/2016. We also use bid and ask prices to calculate the bid-ask spread as a proxy for transaction costs. The data sources for the index and and the bid/ask prices are Eikon Thomson Reuters and Bloomberg respectively.

The daily (percentage) return series is plotted in Figure 1. Visual inspection suggests stationary behaviour (also confirmed by unit root tests not reported for reasons of space).

Figure 1 Relative daily returns (%) over time

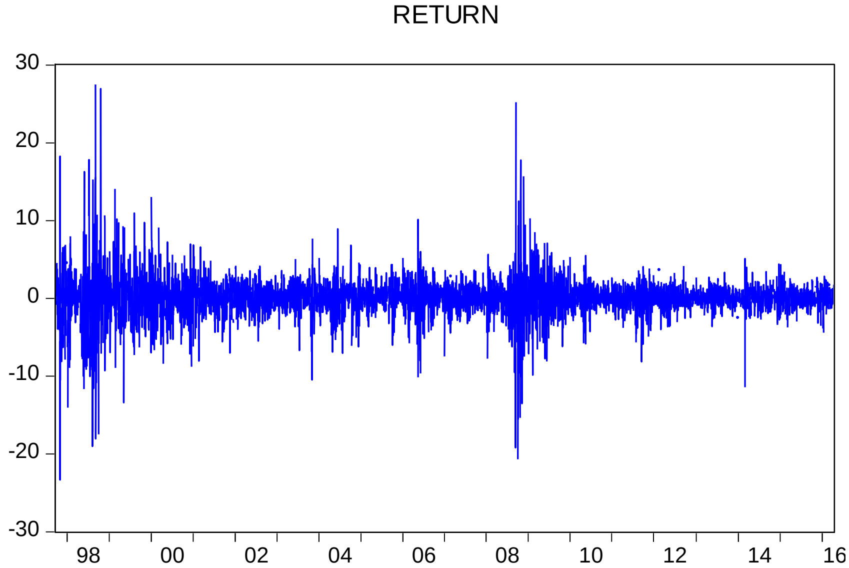


Figure 2 shows average daily returns by month and provides visual evidence of significant differences across months, the worst performance occurring in May and December. It also displays adjusted returns calculated as follows:

$$RS_t = R_t - S_t, \quad (1)$$

where RS_t stands for spread-adjusted returns, R_t for daily returns, and S_t for the bid-ask spread. It appears that once transaction costs are taken into account the January effect disappears.

Figure 2

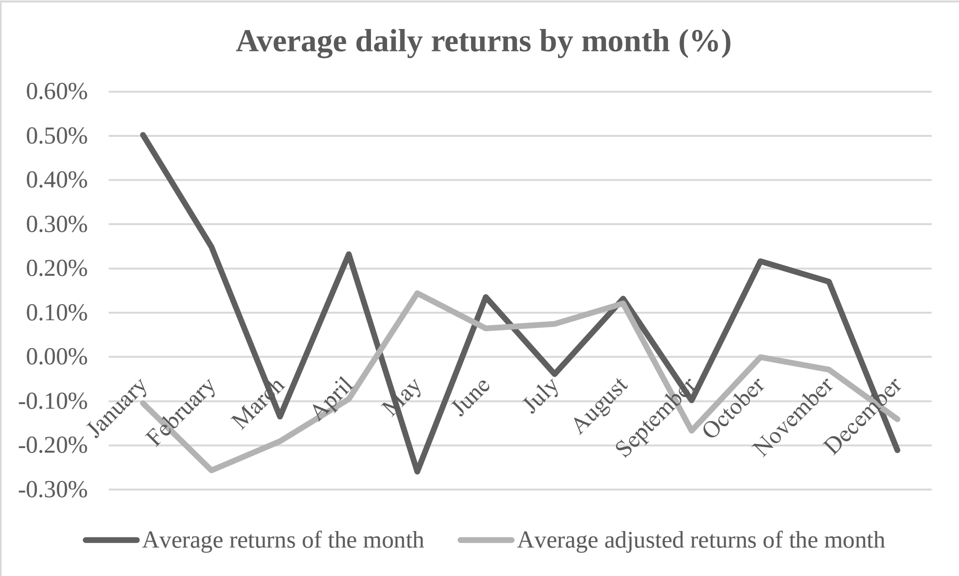


Figure 3 enables us to make a similar comparison between the two series by day of the week. When raw returns are used the best performance is observed at the end of the week (Fridays and Saturdays – there are 25 trading Saturdays in our sample), and the worst on Wednesdays. However, these patterns change completely once transaction costs are introduced: now the best performance occurs in the middle of the week, and the worst at the beginning and the end of the week. This is further evidence of the importance of taking into account transaction costs when analysing anomalies.

Figure 3

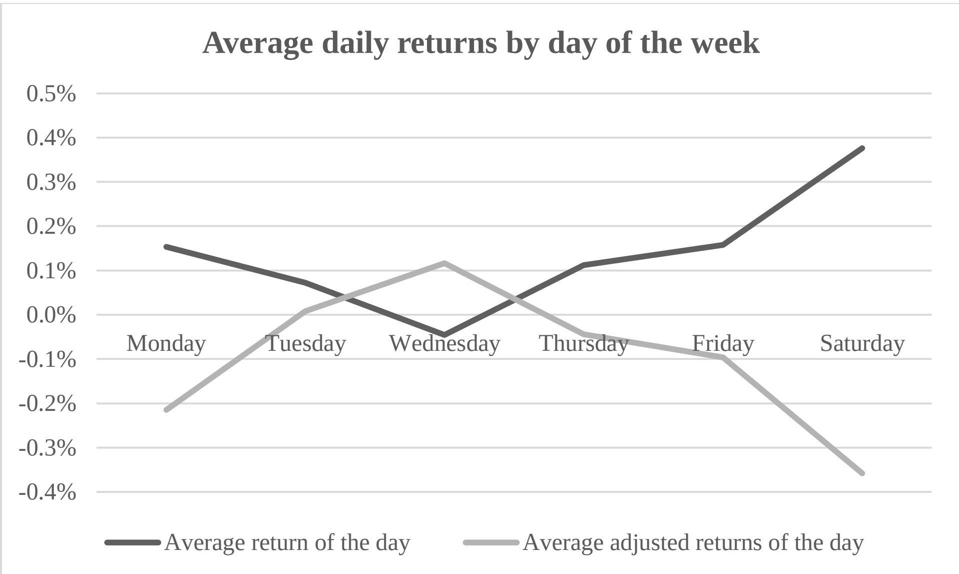
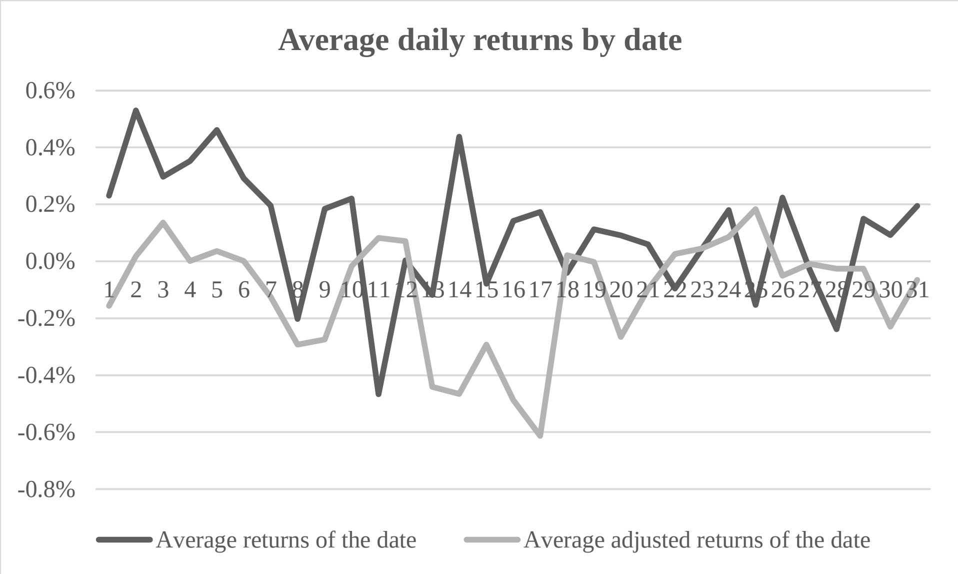


Figure 4 plots average daily returns by date. They appear to be higher in the first week of the month, but only if they are not adjusted.

Figure 4



3. 2 Methodology

We estimate in turn each of the four models used in previous studies on calendar anomalies, i.e. OLS, GARCH, TGARCH, EGARCH.

3.2.1 January effect

3.2.1.1. OLS Regressions

Following Compton (2013), we run the following regression to test for anomalies:

$$H_0: \beta_1 = \beta_2 =..= \beta_{12}$$

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \cdots + \beta_{12} D_{12t} + \varepsilon_t,$$

where the coefficients $\beta_1 \dots \beta_{12}$ represent mean daily returns for each month and each dummy variable $D_1 \dots D_{12}$ is equal to 1 if the return is generated in that month and 0 otherwise, and ε_t is the error term. If the null is rejected than we conclude that seasonality is present and we run a second regression, namely:

$$H_0: \alpha = 0$$

$$R_t = \alpha + \beta_1 D_{1t} + \beta_2 D_{2t} + \cdots + \beta_{11} D_{11t} + \varepsilon_t,$$

where α stands for January returns, the coefficients $\beta_1 \dots \beta_{11}$represent the difference between expected mean daily returns for January and mean daily returns for other months, each dummy variable $D_1 \dots D_{12}$ is equal to 1 if the return is generated in that month and 0 otherwise, and ε_t is the error term.

3.2.1.2 GARCH Model

Given the extensive evidence on volatility clustering in the case of stock returns we follow Levagin (2010), Gregoriou (2004), Yalcin, Yucel (2003), Luo, Gan, Hu, Kao (2009) and Mangala, Lohia (2013) and adopt the following specification.

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \cdots + \beta_{12} D_{12t} + \varepsilon_t,$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma * D(Jan)$$

where ω is an intercept, $\varepsilon_t \sim N(0, \sigma_t^2)$ is the error term, and D(Jan) is a series of dummy variables equal to 1 if the return occurs in that month and zero otherwise.

Since σ_t^2 should be positive, we have the following restrictions: $\omega \geq 0$, $\alpha \geq 0,\ \beta \geq 0$.

3.2.1.3. TGARCH Model

Standard GARCH models often assume that positive and negative shocks have the same effects on volatility, however in practice the latter often have bigger effects. Therefore, following Levagin (2010) we also estimate the following TGARCH model:.

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \cdots + \beta_{12} D_{12t} + \varepsilon_t,$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} + \beta\sigma_{t-1}^2 + \theta * D(Jan),,$$

where I_{t-1}= 1, if $\varepsilon_{t-1} < 0$, and I_{t-1}= 0 otherwise.

The following restrictions apply: $\omega \geq 0$, $\alpha \geq 0,\ \beta \geq 0$, $\alpha + \gamma \geq 0$.

3.2.1.4 EGARCH Model

Another useful framework to analyse volatility clustering is the following EGARCH model:

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \cdots + \beta_{12} D_{12t} + \varepsilon_t,$$

$$\ln(\sigma_t^2) = \omega + \beta\ln(\sigma_{t-1}^2) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \theta * D(Jan),,,$$

where γ captures the asymmetries: if negative shocks are followed by higher volatility than the estimate of γ will be negative. This model does not require any restrictions.

3.2.2 Day-of-the-week effect

3.2.2.1 OLS regressions

Following Compton (2013), we check whether mean daily returns are the same for each day of the week using the following regression:

$$H_0: \beta_1 = \beta_2 =.. = \beta_5$$

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \cdots + \beta_5 D_5 + \varepsilon_t,$$

where the coefficients $\beta_1 \ldots \beta_5$ stand for mean daily returns for each trading day of the week, each dummy variable $D_1 \ldots D_5$ is equal to 1 if the mean daily return occurs on that day and zero otherwise, and ε_t is the error term. If the null is rejected then mean daily returns vary during the week, an anomaly exists and we run the second regression.

$$H_0: \alpha = 0$$

$$R_t = \alpha + \beta_1 D_{1t} + \beta_2 D_{2t} + \cdots + \beta_4 D_{4t} + \varepsilon_t,$$

where α stands for mean daily returns on Mondays, the coefficients $\beta_1 \ldots \beta_4$ for the difference between mean daily returns on Mondays and on other days of the week, each dummy variable $D_1 \ldots D_4$ is equal to 1 if mean daily return occurs on that day and zero otherwise, and ε_t is the error term. Rejection of the null indicates the presence of a day-of-the week effect.

3.2.2.2 GARCH Model

Following again Levagin (2010), Gregriou (2004), Yalcin, Yucel (2003), Luo, Gan, Hu, Kao (2009) and Mangala, Lohia (2013) we use the following specification.

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \cdots + \beta_5 D_5 + \varepsilon_t$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma * D(Mon) + \delta D(Fri) + \theta D(Sat)$$

where ω is an intercept, $\varepsilon_t \sim N(0, \sigma_t^2)$, D(Mon), D(Fri), D(Sat) are the dummy variables, that are set equal to 1 if returns occur on Mondays, Fridays, Saturdays respectively and zero otherwise. Unlike previous studies we also include Saturdays since there are 25 trading Saturdays in the sample.

Since σ_t^2 should be positive, we have the following restrictions: $\omega \geq 0, \alpha \geq 0,\ \beta \geq 0$.

3.2.2.3 TGARCH Model

We estimate the following model:

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \cdots + \beta_5 D_5 + \varepsilon_t$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} + \beta\sigma_{t-1}^2 + \theta * D(Mon) + \delta * D(Fri) + \mu * D(Sat),,$$

where I_{t-1}= 1, if $\varepsilon_{t-1} < 0$, and I_{t-1}= 0 otherwise.

The following restrictions apply: $\omega \geq 0, \alpha \geq 0,\ \beta \geq 0, \alpha + \gamma \geq 0$.

3.2.2.4 EGARCH Model

The specification is the following:

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \cdots + \beta_5 D_5 + \varepsilon_t$$

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \theta * D(Mon) + \delta * D(Fri) + \mu * D(Sat),$$

where γ captures the asymmetric response to shocks: again, if negative shocks have a bigger impact on volatility then the estimate of γ will be negative; no restrictions are required.

3.2.3 Turn-of-the-month effect (TOM effect)

3.2.3.1 OLS Regressions

To analyse the TOM effect, first we run the following regression to determine whether mean daily returns at the turn of the month are significantly different from zero:

$$H_0: \beta_{-9} = \beta_{-8} =..= \beta_9$$

$$R_t = \beta_{-9} D_{-9t} + \beta_{-8} D_{-8t} + \cdots + \beta_8 D_{8t} + \beta_9 D_{9t} + \varepsilon_t,$$

where $\beta_{-9} \ldots \beta_9$ measure mean daily returns for each day around the TOM, the dummy variables $D_{-9} \ldots D_9$ are equal to 1 if the mean daily return occurs on that trading day, and zero otherwise, and ε_t is the error term.

If mean daily returns are significantly different from zero then we run a second regression to test the null hypothesis that those around the TOM are the same as the mean daily returns during the rest-of-the-month (ROM). Specifically, we estimate the following equation:

$$H_0: \beta = 0$$

$$R_t = \alpha + \beta D_{TOM} + \varepsilon_t,$$

where α is the mean return for the ROM period, β is the difference between the mean TOM return and the mean ROM return, D_{TOM} is 1 if returns occurs in the TOM period and zero otherwise, and ε_t is the error term. The turn-of-the month period is defined as days -1…+3.

3.2.3.2 GARCH Model

First, we estimate the following model

$$R_t = \beta_{-9} D_{-9t} + \beta_{-8} D_{-8t} + \cdots + \beta_8 D_{8t} + \beta_9 D_{9t} + \varepsilon_t,$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma_1 D_1 + \gamma_2 D_2 + \cdots + \gamma_{17} D_{17} + \gamma_{18} D_{18},$$

where ω is an intercept, $\varepsilon_t \sim N(0, \sigma_t^2)$, D_1 ... D_{18} are the dummy variables corresponding to each day around the turn of the month that are equal to 1 if returns occur on that day of the month and zero otherwise (D1 = -9, D2 = -8, D3 = -7, D4 = -6, D5 = -5, D6 = -4, D7 = -3, D8 = -2, D9 = -1, D10 = 1, D11 = 2, D12 = 3, D13 = 4, D14 = 5, D15 = 6, D16 = 7, D17 = 8, D18 = 9)

Then we estimate the following model

$$R_t = \alpha + \beta D_{TOM} + \varepsilon_t,$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma * D(TOM),$$

where ω is an intercept, $\varepsilon_t \sim N(0, \sigma_t^2)$, D(TOM) is a dummy variable that is 1, if returns occur on the day around TOM (the last day of the month and the first three days of the month), and zero otherwise.

As usual, since σ_t^2 should be positive, we have the following restrictions: $\omega \geq 0, \alpha \geq 0, \ \beta \geq 0$.

3.2.3.3 TGARCH Model

First, we run

$$R_t = \beta_{-9} D_{-9t} + \beta_{-8} D_{-8t} + \cdots + \beta_8 D_{8t} + \beta_9 D_{9t} + \varepsilon_t,$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \beta \sigma_{t-1}^2 + \theta_1 D_1 + \theta_2 D_2 + \cdots + \theta_{17} D_{17} + \theta_{18} D_{18},$$

where I_{t-1}= 1, if $\varepsilon_{t-1} < 0$, and I_{t-1}= 0 otherwise, D_1 ... D_{18} are the dummy variables corresponding to each day around the turn of the month that are set equal to 1 if returns occurs on that day of the month and zero otherwise.

We then estimate

$$R_t = \alpha + \beta D_{TOM} + \varepsilon_t,$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \beta \sigma_{t-1}^2 + \theta * D(TOM),$$

where I_{t-1}= 1, if $\varepsilon_{t-1} < 0$, and I_{t-1}= 0 otherwise, D(TOM) is a dummy variable that is 1 if returns occur on the days around TOM (the last day of the month and the first three days of the month), and zero otherwise. The usual restrictions apply: $\omega \geq 0, \alpha \geq 0, \ \beta \geq 0, \alpha + \gamma \geq 0$ in both regressions.

3.2.3.4 EGARCH Model

First, we run the following regression

$$R_t = \beta_{-9} D_{-9t} + \beta_{-8} D_{-8t} + \cdots + \beta_8 D_{8t} + \beta_9 D_{9t} + \varepsilon_t,$$

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \theta_1 D_1 + \theta_2 D_2 + \cdots + \theta_{17} D_{17} + \theta_{18} D_{18},$$

where γ captures the asymmetric response to shocks.

Next, we estimate the following regression:

$$R_t = \alpha + \beta D_{TOM} + \varepsilon_t,$$

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \theta * D(TOM),,$$

In each case we focus on both the mean and variance equations, since the variance of returns may also exhibit seasonality.

The next step is to adjust returns by subtracting the bid-ask spreads as a proxy for transaction costs (see Gregoriou et al., 2004 and Caporale et al., 2015), as in equ. (1).

4 Empirical results

4.1 Empirical results without the adjustment

Table 1 reports the evidence on the January effect for the four models, i.e. OLS, GARCH (1,1), TGARCH (1,1), EGARCH (1,1). It is only found in the mean equation of the GARCH and EGARCH models (but not in the conditional variance equations). Table 2 displays the results for the day-of-the week effect. A Monday effect is found in the mean equations of the GARCH and TGARCH models, and a Friday effect in the mean equation of the EGARCH specification as well. A Monday effect is also present in the conditional volatility of returns. The results for the TOM effect are displayed in Table 3 and provide some evidence for it in the conditional volatility of returns. The second model (Table 4) measures the TOM effect by using a single dummy variable for the last day and the first three days of the month, and provides stronger evidence of such an effect.

Table 1

Mean Equation								
	OLS		GARCH		TGARCH		EGARCH	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
JANUARY	0.142	0.975	0.172	2.271**	0.108	1.439	0.142	2.106**
FEBRUARY	0.281	2.013**	0.369	8.534***	0.345	7.917***	0.367	9.173***
MARCH	0.216	1.611	0.018	0.196	-0.045	-0.497	-0.079	-0.841
APRIL	0.119	0.88	0.085	1.043	0.074	0.905	0.063	0.8
MAY	-0.108	-0.755	0.024	0.274	-0.018	-0.197	-0.012	-0.14
JUNE	-0.031	-0.221	0.105	1.039	0.049	0.498	0.018	0.192
JULY	-0.047	-0.347	0.034	0.381	-0.004	-0.047	0.017	0.195
AUGUST	-0.084	-0.619	0.116	1.285	0.069	0.763	0.065	0.826
SEPTEMBER	-0.029	-0.213	0.067	0.864	0.071	0.904	0.016	0.227
OCTOBER	0.074	0.565	0.229	2.854***	0.181	2.311**	0.134	1.922*
NOVEMBER	0.064	0.47	0.089	1.064	0.041	0.494	0.037	0.517
DECEMBER	0.165	1.231	0.146	2.009**	0.166	2.077**	0.199	3.261***
Variance Equation								
	OLS		GARCH		TGARCH		EGARCH	
			Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
C			0.083	10.059***	0.084	10.771***	-0.156	-24.643***
ARCH			0.128	24.147***	0.088	12.776***	0.24	30.584***
GARCH			0.863	163.972***	0.866	168.381***	0.983	763.35***
Leverage					0.071	8.034***	-0.045	-8.793***
JANUARY			-0.006	-0.261	-0.014	-0.565	-0.006	-0.595

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Table 2

Mean Equation								
	OLS		GARCH		TGARCH		EGARCH	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
MONDAY	0.145	1.606	0.135	2.373**	0.108	1.935*	0.057	1.063
TUESDAY	0.032	0.367	0.078	1.567	0.035	0.697	0.07	1.611
WEDNESDAY	-0.08	-0.905	0.031	0.601	0.003	0.049	0.004	0.088
THURSDAY	0.078	0.889	0.161	3.221***	0.128	2.477**	0.119	2.637***
FRIDAY	0.127	1.424	0.181	3.262***	0.162	2.92***	0.174	3.607***
SATURDAY	0.703	1.524	0.319	0.778	0.322	0.804	0.323	0.929
Variance Equation								
	OLS		GARCH		TGARCH		EGARCH	
			Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
C			0.047	1.605	0.072	2.435**	-0.186	-13.704***
ARCH			0.127	23.963***	0.09	12.903***	0.241	30.324***
GARCH			0.862	162.742***	0.863	165.634***	0.982	790.636***
Leverage					0.067	7.605***	-0.04	-7.846***
MONDAY			0.234	3.791***	0.175	2.757***	0.18	5.257***
FRIDAY			-0.017	-0.156	-0.068	-0.636	-0.016	-0.341
SATURDAY			0.165	0.616	0.081	0.3	-0.006	-0.063

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Table 3

Mean Equation								
	OLS		GARCH		TGARCH		EGARCH	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
D1	0.181	0.736	-0.015	-0.07	0.08	0.4	0.137	1.274
D2	0.181	2.343**	0.225	0.579	0.437	1.048	0.133	1.313
D3	0.18	-0.01	0.022	0.07	-0.022	-0.064	0.052	0.5
D4	0.18	0.383	0.268	0.953	0.086	0.294	0.212	2.136**
D5	0.18	-0.594	-0.099	-0.323	-0.079	-0.243	-0.08	-0.941
D6	0.18	-1.532	-0.282	-1.107	-0.246	-0.943	-0.176	-1.501
D7	0.18	0.894	0.077	0.312	0.126	0.515	0.059	0.572
D8	0.18	0.736	0.019	0.072	0.05	0.176	0.026	0.276
D9	0.18	0.849	0.136	0.565	0.144	0.779	0.043	0.389
D10	0.18	0.422	0.204	0.796	0.132	0.497	0.085	0.776
D11	0.18	0.478	0.107	0.397	0.081	0.294	0.17	1.665*
D12	0.18	1.028	0.151	0.535	0.153	0.533	0.15	1.452
D13	0.18	0.035	-0.041	-0.163	0.009	0.034	-0.006	-0.042
D14	0.18	1.224	0.131	0.468	0.195	0.73	0.187	1.807*
D15	0.18	0.609	0.211	0.649	0.1	0.307	0.218	1.99**
D16	0.18	0.166	0.075	0.346	0.079	0.458	0.143	1.594
D17	0.18	-0.386	-0.056	-0.176	-0.07	-0.225	0.122	1.52
D18	0.18	-0.88	-0.094	-0.289	-0.101	-0.303	0.037	0.354

Table 3 (continued)

Variance Equation						
OLS	GARCH		TGARCH		EGARCH	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
C	6.48	11.904***	6.468	11.003***	-0.198	-10.436***
ARCH	0.152	9.479***	0.143	7.091***	0.236	22.287***
GARCH	0.565	16.274***	0.566	15.684***	0.986	565.039***
Leverage			0.046	1.914*	-0.038	-6.733***
D1	-6.072	-8.878***	-6.013	-6.955***	0.213	2.398**
D2	-0.765	-0.919	-0.839	-0.859	-0.137	-1.255
D3	-2.672	-2.353**	-2.199	-1.56	-0.055	-0.506
D4	-2.776	-3.057***	-2.615	-2.662***	0.424	3.873***
D5	-3.829	-4.199***	-3.674	-3.828***	-0.337	-2.991***
D6	-2.999	-4.023***	-3.063	-3.586***	0.209	2.113**
D7	-3.135	-3.651***	-3.128	-2.844***	0.2	2.085**
D8	-3.882	-4.352***	-3.572	-3.225***	-0.263	-2.502**
D9	-4.198	-5.601***	-4.032	-3.404***	-0.026	-0.241
D10	-3.678	-3.876***	-3.659	-3.425***	0.099	1.002
D11	-3.464	-3.746***	-3.473	-3.509***	0.17	1.844*
D12	-3.406	-3.846***	-3.54	-3.798***	-0.397	-4.628***
D13	-3.165	-4.151***	-3.088	-3.38***	0.325	3.696***
D14	-3.68	-4.66***	-3.539	-2.992***	0.037	0.468
D15	-1.731	-1.807*	-1.876	-1.709*	0.349	4.298***
D16	-2.873	-6.016***	-3.026	-3.068***	0.178	1.667*
D17	-4.439	-4.822***	-4.338	-3.19***	-0.261	-2.839***
D18	-3.018	-2.663***	-3.194	-2.651***	0.098	1.266

D1 = -9, D2 = -8, D3 = -7, D4 = -6, D5 = -5, D6 = -4, D7 = -3, D8 = -2, D9 = -1, D10 = 1, D11 = 2, D12 = 3, D13 = 4, D14 = 5, D15 = 6, D16 = 7, D17 = 8, D18 = 9

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Table 4

Mean Equation								
	OLS		GARCH		TGARCH		EGARCH	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
C	0.043	0.953	0.095	3.599***	0.063	2.295**	0.065	2.512**
TURNOFMONTH	0.089	0.953	0.102	1.707*	0.1	1.709*	0.12	2.196**
Variance Equation								
	OLS		GARCH		TGARCH		EGARCH	
			Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
C			0.069	6.21***	0.069	6.397***	-0.152	-21.885***
ARCH			0.129	25.11***	0.091	13.29***	0.237	31.017***
GARCH			0.861	171.256***	0.862	171.006***	0.982	846.509***
Leverage					0.068	8.149***	-0.039	-8.331***
TURNOFMONTH			0.091	2.641***	0.097	2.878***	0.003	0.204

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

4.2 Empirical results with the adjustment

Table 5 suggests that a January effect is present in the variance equation of the GARCH and TGARCH models. However, the negativity restrictions for these models are not satisfied; this issue does not arise in the case of the EGARCH model, that does not have any restrictions on its coefficients. Table 6 shows that a Monday effect is only present in the conditional variance equation of the EGARCH model. Table 7 provides less evidence of a TOM effect in the conditional variance equation compared to Table 3. The results for the second model to test the TOM effect are reported in Table 8; this is now not present in the mean equation, but can still be found in the variance equation, except in the case of the EGARCH model.

Table 5

Mean Equation								
	OLS		GARCH		TGARCH		EGARCH	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
JANUARY	0.258	1.49	0.218	0.953	0.191	0.82	0.172	0.89
FEBRUARY	0.108	0.695	0.049	0.271	0.092	0.54	0.245	1.686*
MARCH	-0.178	-1.254	-0.344	-2.61***	-0.258	-2.105**	-0.378	-3.159***
APRIL	-0.061	-0.398	-0.05	-0.295	-0.052	-0.328	-0.07	-0.582
MAY	0.03	0.179	0.023	0.138	0.016	0.106	0.035	0.24
JUNE	0.074	0.44	0.084	0.403	0.1	0.518	-0.086	-0.62
JULY	-0.037	-0.237	-0.043	-0.226	-0.044	-0.251	-0.161	-1.473
AUGUST	0.07	0.43	0.067	0.342	0.084	0.468	0.033	0.288
SEPTEMBER	0.036	0.225	0.056	0.312	0.059	0.356	-0.102	-0.86
OCTOBER	0.186	1.182	0.202	1.052	0.194	1.09	0.057	0.516
NOVEMBER	0.073	0.436	0.059	0.273	0.055	0.277	0.295	2.387**
DECEMBER	-0.126	-0.787	-0.097	-0.722	-0.069	-0.534	0.019	0.141
Variance Equation								
	OLS		GARCH		TGARCH		EGARCH	
			Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
C			2.358	12.12***	1.748	3.25***	-0.003	-0.301
ARCH			0.058	2.087**	0.11	2.149**	0.017	1.423
GARCH			-0.468	-4.372***	-0.21	-0.63	0.976	108.78***
Leverage					-0.041	-0.664	-0.098	-6.064***
JANUARY			1.39	2.193**	1.139	1.937*	0.029	1.106

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Table 6

Mean Equation								
	OLS		GARCH		TGARCH		EGARCH	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
MONDAY	-0.096	-0.933	0.111	-0.703	-0.204	-1.344	-0.094	-0.672
TUESDAY	0.195	1.901*	0.132	1.548	0.245	1.347	0.127	1.407
WEDNESDAY	0.006	0.061	0.034	0.346	0.026	0.131	0.051	0.524
THURSDAY	0.022	0.215	0.025	-0.264	0.039	0.205	-0.006	-0.064
FRIDAY	0.012	0.111	0.026	0.257	0.018	0.119	0.075	0.72
SATURDAY	-0.18	-0.139			-0.17	-0.01	-0.18	-931.154***
Variance Equation								
	OLS		GARCH		TGARCH		EGARCH	
			Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
C			1.419	6.490***	1.395	0.851	0.105	0.867
ARCH			0.136	3.573***	0.032	0.539	0.3	4.709***
GARCH			0.130	1.296	0.523	0.853	-0.003	-0.018
Leverage					-0.043	-0.74	0.024	0.559
MONDAY			1.302	8.211***	-0.092	-0.211	0.529	5.984***
FRIDAY			0.037	0.226	-0.718	-1.448	0.063	0.529
SATURDAY			-1.23	-0.339	-2.602	-0.701	-22.779	-6.113***

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Table 7

Mean Equation								
	OLS		GARCH		TGARCH		EGARCH	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
D1	0.26	1.242	0.194	1.054	0.2	1.017	0.113	0.485
D2	0.118	0.559	0.12	0.677	0.119	0.663	0.097	0.55
D3	0.035	0.163	-0.033	-0.132	-0.03	-0.117	-0.164	-0.715
D4	0.319	1.505	0.322	1.551	0.319	1.563	0.307	1.519
D5	-0.219	-1.033	-0.227	-1.245	-0.229	-1.235	-0.275	-1.544
D6	-0.329	-1.553	-0.288	-1.705*	-0.293	-1.744*	-0.234	-1.397
D7	-0.285	-1.365	-0.209	-0.922	-0.221	-0.995	-0.228	-1.185
D8	0.189	0.903	0.126	0.441	0.127	0.46	0.232	1.475
D9	0.297	1.419	0.243	1.279	0.226	0.968	0.32	1.394
D10	-0.134	-0.64	-0.185	-0.811	-0.208	-0.92	-0.182	-0.816
D11	0.146	0.698	0.182	0.61	0.199	0.683	0.259	1.298
D12	0.474	2.266**	0.446	1.426	0.421	1.381	0.228	1.066
D13	-0.25	-1.198	-0.294	-0.595	-0.309	-0.638	-0.305	-0.502
D14	0.227	1.097	0.332	0.717	0.362	0.795	0.326	1.75*
D15	-0.032	-0.153	-0.084	-0.239	-0.074	-0.215	-0.059	-0.365
D16	0.002	0.008	-0.033	-0.164	-0.049	-0.204	0.036	0.199
D17	0.074	0.357	0.029	0.099	0.004	0.015	0.043	0.313
D18	-0.046	-0.223	-0.029	-0.088	-0.004	-0.013	-0.045	-0.269

Table 7 (continued)

Variance Equation						
OLS	GARCH		TGARCH		EGARCH	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
C	1.511	2.703***	1.508	2.641***	-0.107	-1.583
ARCH	0.077	1.725*	0.077	1.425	0.146	3.441***
GARCH	0.563	2.974***	0.554	2.88***	0.949	41.047***
Leverage			-0.003	-0.045	-0.065	-2.658***
D1	-0.915	-1.693*	-0.9	-1.662*	0.488	1.503
D2	-1.494	-2.983***	-1.459	-2.928***	-0.442	-1.189
D3	-0.851	-1.63	-0.819	-1.617	0.024	0.068
D4	-0.504	-0.894	-0.531	-0.959	0.389	1.015
D5	-1.024	-1.765*	-0.999	-1.71*	0.065	0.159
D6	-1.392	-2.673***	-1.364	-2.67***	-0.107	-0.275
D7	-0.964	-1.819*	-0.95	-1.774*	0.287	1.041
D8	-1.128	-1.937*	-1.124	-1.955*	-0.562	-2.005**
D9	-0.883	-1.475	-0.879	-1.693*	-0.077	-0.254
D10	-0.803	-1.484	-0.784	-1.477	0.285	0.999
D11	-0.789	-1.09	-0.766	-1.11	-0.111	-0.348
D12	-1.076	-1.314	-1.086	-1.395	-0.823	-2.965***
D13	0.07	0.1	0.109	0.168	1.37	5.261***
D14	-0.148	-0.138	-0.209	-0.215	-0.05	-0.145
D15	-0.364	-0.52	-0.37	-0.534	-0.243	-0.601
D16	-0.667	-0.856	-0.663	-1.166	0.512	1.265
D17	-1.05	-1.977**	-1.038	-2.002**	-0.069	-0.197
D18	-1.391	-2.239**	-1.395	-2.336**	-0.687	-2.169**

D1 = -9, D2 = -8, D3 = -7, D4 = -6, D5 = -5, D6 = -4, D7 = -3, D8 = -2, D9 = -1, D10 = 1, D11 = 2, D12 = 3, D13 = 4, D14 = 5, D15 = 6, D16 = 7, D17 = 8, D18 = 9

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Table 8

Mean Equation								
	OLS		GARCH		TGARCH		EGARCH	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
C	0.004	0.073	0.013	0.285	0.004	0.091	0.008	0.147
TURNOFMONTH	0.101	0.936	0.084	0.622	0.077	0.593	0.073	0.649
Variance Equation								
	OLS		GARCH		TGARCH		EGARCH	
			Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
C			0.303	3.658***	0.258	3.443***	-0.065	-2.058**
ARCH			0.141	3.744***	0.09	2.614***	0.139	3.194***
GARCH			0.625	9.268***	0.67	10.561***	0.888	27.265***
Leverage					0.082	1.578	-0.098	-5.015***
TURNOFMONTH			0.46	7.323***	0.387	5.515***	0.055	1.179

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Table 9 summarises the empirical findings. In brief, evidence of a January effect is found for the raw returns when using GARCH and EGARCH specifications; however, it disappears when transaction costs are introduced. A day-of-the-week effect is also detected when estimating GARCH and TARCH models for the raw series, but again it disappears when using adjusted returns. Similarly, a turn-of-the month effect is found only for the raw data when adopting GARCH, TGARCH and EGARCH specifications.

Table 9 Summary of the results

	OLS		GARCH		TGARCH		EGARCH	
	without adj.	with adj.	without adj.	with adj.	without adj.	without adj.	with adj.	without adj.
January effect	-	-	+	-	-	-	+	-
Day-of-the-week effect	-	-	+	-	+	-	-	-
Turn-of-the month effect	-	-	+	-	+	-	+	-

5 Conclusions

This paper investigates calendar anomalies (specifically, January, day-of-the-week, and turn-of-the-month effects) in the Russian stock market analysing the behaviour of the MICEX index over the period 22/09/1997-14/04-2016 by estimating OLS, GARCH, EGARCH and TGARCH models. The empirical results show that once transaction costs are taken into account such anomalies disappear, and therefore there is no strategy based on them that could beat the market and result in abnormal profits, which would amount to evidence against the EMH. Therefore the findings of previous studies overlooking transaction costs were misleading: when adjusting returns by using bid-ask spreads as a proxy for such costs (see Gregoriou et al., 2004) the evidence for calendar anomalies and profitable strategies based on them vanishes, suggesting that markets (specifically the Russian stock market in our case) might in fact be informationally efficient.

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