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Abstract

This research note investigates whether or not calendar anomalies (such as the January, day-of-the-week and turn-of-the-month effects) characterize 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 Sept. 1997–Apr. 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.

1. Introduction

There is a large body of 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 these types of anomalies has been seen as inconsistent with the efficient market hypothesis (EMH — see Fama, 1965), since it would imply that trading strategies that exploit 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 behavior of asset returns. Calendar anomalies might disappear once transaction costs are taken into

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account, the implication being that in fact there are no exploitable profit opportunities based on transaction costs.

The present study examines calendar anomalies in the Russian stock market by incorporating transaction costs in the estimated models (following Gregoriou et al., 2004 and Caporale et al., 2016), and therefore, it expands previous studies on anomalies in this market, such as Compton et al. (2013), not taking into account transaction costs. Specifically, four models are estimated: OLS, GARCH, TGARCH and EGARCH.

The structure of the note is as follows: Section 2 briefly reviews 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 studies such as Rozeff and Kinney (1976) and Lakonishok and Smith (1988) using long series to avoid the problems of data snooping, noise and selection bias, and finding evidence of various calendar anomalies, namely January, day-of-the-week and turn-of-the-month (TOM) effects. Thaler (1987) reported that the January effect mainly characterizes shares of small companies, while 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 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 (2009) found a January effect in 7 out of 10 Asia-Pacific countries. Darrat et al. (2013) analyzed an extensive dataset including 34 countries and reported a January effect in all except three of them (Denmark, Ireland, Jordan). Yalcin and Yucel (2003) analyzed 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 TOM 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. (2016) reached the same conclusion in the case of the Ukrainian stock market using a trading robot approach.

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, Dubois and Louvet (1996) found that in other markets such as France, Turkey, Japan, Singapore and Australia, the highest negative returns appear on Tuesdays; this may be explained by the fact that these markets are influenced by negative news in the U.S. 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 Raj and Kumari, 2006); however, these might differ across countries. Rystrom and Benson (1989)

argued that investors are irrational and their sentiments vary on different days of the week, which might explain the day-of-the week effect. Finally, Pettengill (2003) claimed that they 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 analyzed is the capitalization-weighted MICEX market index. The sample includes 4,633 observations on (close-to-close) daily returns and covers the period from 22.09.1997 (when this index was created) until 14.04.2016. We also use bid and ask prices to calculate the bid-ask spread as a proxy for transaction costs. The data source for the index is Bloomberg,

Returns were calculated using the following formula:

$$R_t = \frac{P_t^{close} - P_{t-1}^{close}}{P_{t-1}^{close}}, \tag{1}$$

where P_t is the index value in period t. Dividends are not included because the trading strategy is considered daily.

The data source for bid-ask prices is Thompson Reuters. Since the MICEX index is a composite index of 50 Russian tradable companies, the bid-ask spread was calculated as a weighted spread of the individual stocks using the following formula:

$$S = \omega_1 S_1 + \omega_2 S_2 + ... + \omega_{49} S_{49} + \omega_{50} S_{50}, \tag{2}$$

where S_t is the bid-ask spread used below for adjustment purposes and ω_t is the share of the stock in the index.

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

Following Gregoriou et al. (2004), the adjusted returns were calculated as:

$$RS_t = \frac{(P_t^{close} - S_t) - (P_{t-1}^{close} - S_{t-1})}{(P_{t-1}^{close} - S_{t-1})}, \tag{3}$$

where RS_t stands for spread-adjusted returns, R_t for daily returns, and S_t for the bid-ask spread. The adjustment is made because investors deduct transaction
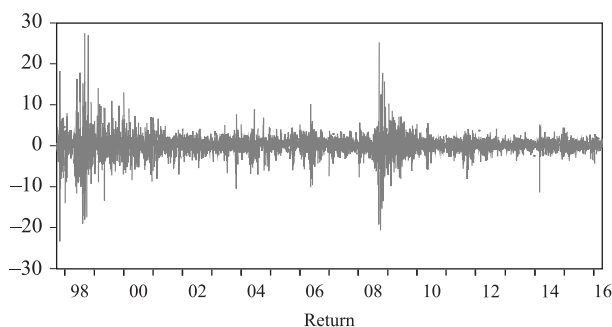

Fig. 1. Relative daily returns (%) over time.

Table 1
Descriptive statistics (%).

	Mean	St. error	Median	Variance	Kurtosis	Skewness	Min	Max
Raw returns	0.10	0.04	0.12	0.07	0.18	0.84	−20.81	31.65
Adjusted returns	0.03	0.05	0.09	1.66	8.33	0.77	−21.47	28.16

costs from returns to calculate the effective rate of return on their investments. The bid-ask spread is a good proxy for the variable aspect of transaction costs.

Table 1 reports descriptive statistics for both raw and adjusted returns. It shows that the average return is seven basis points lower for adjusted returns than for raw returns.

3.2. Methodology

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

3.2.1. OLS regressions

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

$$H_0 : \beta_1 = \beta_2 = ... = \beta_{12}, \tag{4}$$

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + ... + \beta_{12} D_{12t} + \varepsilon_t, \tag{5}$$

where the coefficients $\beta_1 ... \beta_{12}$ represent mean daily returns for each month, each dummy variable $D_1 ... D_{12}$ 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, we conclude that seasonality is present and run a second regression:

$$H_0 : \alpha = 0, \tag{6}$$

$$R_t = \alpha + \beta_1 D_{1t} + \beta_2 D_{2t} + ... + \beta_{11} D_{11t} + \varepsilon_t, \tag{7}$$

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

3.2.2. The GARCH model

Given the extensive evidence on volatility clustering in the case of stock returns, we follow Levagin and Poldin (2010), Gregoriou et al. (2004), Yalcin and Yucel (2003) and adopt the following specification:

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + ... + \beta_{12} D_{12t} + \varepsilon_t, \tag{8}$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma * D(Jan), \tag{9}$$

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

3.2.3. The TGARCH model

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

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + ... + \beta_{12} D_{12t} + \varepsilon_t, \tag{10}$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \beta \sigma_{t-1}^2 + \theta * D(Jan), \tag{11}$$

where $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, and 0 otherwise.
The following restrictions apply: $\omega \geq 0, \alpha \geq 0, \beta \geq 0, \alpha + \gamma \geq 0$.

3.2.4. The EGARCH model

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

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

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \theta * D(Jan), \tag{13}$$

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

We use the same approach to test for day-of-the-week and TOM effects. The exact specification for each model is given in Table 2. The only difference from the previous case is that for the day-of-the-week effect, $\beta_1 ... \beta_5$ stand for mean daily returns for each trading day of the week, and for the TOM effect, $\beta_{-9} ... \beta_9$ measure the mean daily returns for each day around the TOM.

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., 2016), as in (3).

4. Empirical results

For brevity's sake, we only include one table reporting the estimation results for raw and subsequent adjusted returns. All other results are available from the authors upon request. We also provide a summary table for the complete set of results.

Table 2
Model specifications.

	Day-of-the-week effect	TOM effect
OLS	$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + ... + \beta_5 D_5 + \varepsilon_t$	$R_t = \beta_{-9} D_{-9t} + \beta_{-8} D_{-8t} + ... + \beta_8 D_{8t} + \beta_9 D_{9t} + \varepsilon_t$
GARCH	$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma * D(Mon) +$ $+ \delta * D(Fri) + \theta * D(Sat)$	$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma_1 D_1 + \gamma_2 D_2 + ... +$ $+ \gamma_{17} D_{17} + \gamma_{18} D_{18}$
TGARCH	$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \beta \sigma_{t-1}^2 +$ $+ \theta * D(Mon) + \delta * D(Fri) + \mu * D(Sat)$	$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \beta \sigma_{t-1}^2 + \theta_1 D_1 +$ $+ \theta_2 D_2 + ... + \theta_{17} D_{17} + \theta_{18} D_{18}$
EGARCH	$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} +$ $+ \theta * D(Mon) + \delta * D(Fri) + \mu * D(Sat)$	$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} +$ $+ \theta_1 D_1 + \theta_2 D_2 + ... + \theta_{17} D_{17} + \theta_{18} D_{18}$

Table 3
TOM effect before adjustment.

	OLS		GARCH		TGARCH		EGARCH	
	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
Mean Equation								
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	0.880	0.085	1.043	0.074	0.905	0.063	0.800
MAY	−0.108	−0.755	0.024	0.274	−0.018	−0.197	−0.012	−0.140
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	0.470	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								
C			0.083	10.059***	0.084	10.771***	−0.156	−24.643***
ARCH			0.128	24.147***	0.088	12.776***	0.240	30.584***
GARCH			0.863	163.972***	0.866	168.381***	0.983	763.350***
Leverage					0.071	8.034***	−0.045	−8.793***
JANUARY			−0.006	−0.261	−0.014	−0.565	−0.006	−0.595

*** Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

4.1. Empirical results without adjustment

Table 3 reports the evidence on the January effect for the four models (OLS, GARCH (1,1), TGARCH (1,1), EGARCH (1,1)). This effect is only found in the mean equation of the GARCH and EGARCH models (but not in the conditional variance equations). Concerning 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 is observed 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 provide some evidence for it in the conditional volatility of returns. The second model, which measures the TOM effect by using a single dummy variable for the last day and the first three days of the month, provides stronger evidence of such an effect.

4.2. Empirical results with the adjustment

Table 4 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, which does not have any restrictions on its coefficients. A Monday effect is only present in the conditional variance equation of the EGARCH model. There is less evidence of a TOM effect in the conditional variance equation compared to the case of raw returns. The results based on the second TOM specification suggest that it is not present in the mean equation, but it can still be found in the variance equation, except in the case of the EGARCH model.

Table 5 summarizes the complete set of results. In brief, evidence of a January effect is found for the raw returns when using GARCH and EGARCH specifica-

Table 4
TOM effect after adjustment.

	OLS		GARCH		TGARCH		EGARCH	
	Coef	t–Stat	Coef	t–Stat	Coef	t–Stat	Coef	t–Stat
Mean Equation								
JANUARY	0.258	1.490	0.218	0.953	0.191	0.820	0.172	0.890
FEBRUARY	0.108	0.695	0.049	0.271	0.092	0.540	0.245	1.686[*]
MARCH	−0.178	−1.254	−0.344	−2.610[***]	−0.258	−2.105[**]	−0.378	−3.159[***]
APRIL	−0.061	−0.398	−0.050	−0.295	−0.052	−0.328	−0.070	−0.582
MAY	0.030	0.179	0.023	0.138	0.016	0.106	0.035	0.240
JUNE	0.074	0.440	0.084	0.403	0.100	0.518	−0.086	−0.620
JULY	−0.037	−0.237	−0.043	−0.226	−0.044	−0.251	−0.161	−1.473
AUGUST	0.070	0.430	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	−0.860
OCTOBER	0.186	1.182	0.202	1.052	0.194	1.090	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								
C			2.358	12.120[***]	1.748	3.250[***]	−0.003	−0.301
ARCH			0.058	2.087[**]	0.110	2.149[**]	0.017	1.423
GARCH			−0.468	−4.372[***]	−0.210	−0.630	0.976	108.780[***]
Leverage					−0.041	−0.664	−0.098	−6.064[***]
JANUARY			1.390	2.193[**]	1.139	1.937[*]	0.029	1.106

[***] Significant at the 1% level, [**] significant at the 5% level, [*] significant at the 10% level.

Table 5
Summary of the results.

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

tions; however, the evidence 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 TOM effect is found only for the raw data when adopting GARCH, TGARCH and EGARCH specifications.

5. Conclusions

This paper investigates calendar anomalies (specifically, January, day-of-the-week, and TOM effects) in the Russian stock market, analyzing the behavior 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. Therefore, there is no strategy based on anomalies that could beat the market and result in abnormal profits, which would amount to evidence against the EMH. Therefore, the findings of previous studies, such as Compton et al. (2013), that overlook 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) might, in fact, be informationally efficient.

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