Reverse TOM Effect in May on United States capital market

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Abstract: Some circumstances could favor the increase of stock returns at the turn-of-the month. However, in the case of May, the influence of these circumstances could interfere with the selling stocks impact in the Halloween strategies framework. This paper approaches the behavior of returns from United States capital market in a time interval that starts in the last trading day of April, and it ends in the fourth trading day of May. For the period January 2010 – June 2025 we found abnormal low returns in this time interval.

Keywords: Turn-of-the month effect; Halloween strategies; United States capital market

JEL: G40, G10, G14

1. INTRODUCTION

The turn-of-the month (TOM) effect refers to abnormal high stock returns in a time interval that includes the first trading days of a month and the last trading days of the previous month (e.g. Ariel, 1987; Lakonishok and Smidt, 1988). In the financial markets literature there were revealed several circumstances that could favor this calendar anomaly: the investors' reactions to the news about macroeconomic indicators, to companies' results or to public announcements of the corporate strategic investment decisions, the standardizations of some payments, the practice of window dressing, the transactions performed to diminish the tax liabilities etc. (e.g. Brown et al., 1983; Jansson, 1983; Lakonishok and Smidt, 1986; Ogden, 1987; Lakonishok and Smidt, 1988; Ogden, 1990; Woolridge & Snow, 1990; Lakonishok et al., 1991; Donders et al., 2000; Dumontier & Raffournier, 2002; Jones et al., 2004; Nikkinen et al., 2007).

The persistence in time of TOM Effect is a controversial subject in the financial literature. The presence of this form of seasonality on United States capital market was confirmed by numerous investigations (e.g. Agrawal and Tandon, 1994; Pettengill and Jordan, 1988; Ogden, 1990; Ziemba and Hensel, 1994; Hensel et al., 2000; Kunkel et al., 2003; Dzhabarov and Ziemba, 2010; Sharma and Narayan, 2014). There are, however, studies that concluded that TOM Effect disappeared after it had become public (Maberly and Waggoner, 2000; Han et al., 2025).

A previous investigation found some particularities of TOM effect for different durations of the year (e.g. Stefanescu and Dumitriu, 2024). In this paper we study the behavior of returns from United States capital market, in a time interval that starts in the last trading day of April and it ends in the fourth trading day of May. In this time interval, the influence of circumstances specific to the TOM effect could collide with the impact of selling stocks in the framework of Halloween strategies.

The well-known Halloween strategies are based on the old saying „Sell in May and go away", which refers to the belief among many investors that May could be the start of a bear market. To avoid the losses, they sell stocks, and their transactions could lead to a decline of stocks returns. The bear market is supposed to last until autumn when the investors are expected to buy stocks. Bouman and Jacobsen (2002) documented the Halloween Effect, a calendar anomaly describing the pattern of stock returns to be significantly lower in the May - October time interval than in the rest of the year. Many studies concluded that form of seasonality was persistent in time (e.g. Jacobsen and Visaltanachoti, 2009; Haggard and Witte, 2010; Andrade et al., 2013; Lloyd et al., 2017; Arendas et al., 2018; Magnusson, 2021; Zhang and Jacobsen, 2021). However, other investigations found that Halloween Effect weakened or even disappeared after it had been published (e.g. Dichtl and Drobetz, 2015; Degenhardt and Auer, 2018).

A Halloween strategy contains two main phases. In the first one, the investors buy stocks in November or in the following months. The second phase consists in selling the stocks in April or May (e.g. Bouman and Jacobsen, 2002; Swinkels & Van Vliet, 2012). The beginning of such transactions could cause abnormal returns of stocks. A previous study found that, in the first days of purchase transactions associated to the Halloween strategies, the returns from United States capital market were consistently high (e.g. Stefanescu and Dumitriu, 2025). In this paper we investigate whether, especially in the first days, the selling transactions, made to apply such strategies, have a significant influence on the returns.

This investigation covers the period January 2010 - June 2025 and it uses four major indexes from United States capital market. The rest of this paper is organized as follows: the second part provides a description of data and methodology employed to investigate the presence of abnormal returns on the last trading day of April and on the first four trading days of May, the third part presents empirical results, and the fourth part concludes.

2. DATA AND METHODOLOGY

2.1. Data Description

To study the impact of selling transactions associated with the Halloween strategies on US capital market, we employ the daily closing values of four major indexes: Standard & Poor's 500 (S&P 500), Dow Jones Industrial Average (DJIA), NASDAQ Composite (NASDAQ) and Russell 2000. The source of data is Yahoo! Finance. We compute the log returns of these indexes using the formula:

$$r_{j,t} = [\ln(P_{j,t}) - \ln(P_{j,t-1})] \times 100 \quad (1)$$

in which $P_{j,t}$ and $P_{j,t-1}$ are the closing prices of the index j from the days t and t-1, respectively.

Tab. 1 reports the descriptive statistics of returns. NASDAQ has the highest average and Russell 2000 the lowest. The values of standard deviation and the interquartile range suggest the return of Russell 2000 has the highest volatility. The Jarque-Bera tests didn't confirm, for none of the four indexes, the hypothesis of returns normal distribution.

Tab. 1. Descriptive statistics of the returns

Index	S&P 500	DJIA	NASDAQ	Russell 2000
Mean	0.0441	0.0370	0.0563	0.0320
Median	0.0695	0.0630	0.1068	0.0855
Minimum	-12.7652	-13.8418	-13.1492	-15.3991
Maximum	9.0895	10.7643	11.4784	8.9763
Std. Dev.	1.1054	1.0594	1.3048	1.4451
IQ range	0.9552	0.9166	1.2194	1.4908
Jarque-Bera test	29366.0***	60231.1***	11124.2***	13029.8***

Note: *** means significant at 0.01 level.

The Augmented Dickey – Fuller unit root tests were employed to study the stationarity of returns (e.g. Dickey and Fuller, 1979; Dickey and Fuller, 1981). The results indicate that returns of the four indexes are stationary (Tab. 2).

Tab. 2. Results of ADF tests

Index	Test without constant		Test with constant	
	Number of lags	Test statistic	Number of lags	Test statistic
S&P 500	11	-17.6059***	11	-17.8323***
DJIA	10	-18.6256***	10	-18.7875***
NASDAQ	9	-19.7014***	9	-19.9481***
Russell 2000	9	-19.5061***	9	-19.5116***

Notes: The optimum number of lags was identified by Akaike (1974) Information Criterion; *** means significant at 0.01 level.

2.2. Methodology

In this investigation we use two time intervals:

- ToMay, which starts in the last trading day of April and it ends in the fourth trading day of May;
- R_ToMay, which comprises the trading days of a year that are not included in ToMay time interval.

To study the returns from the two time intervals, we use OLS models with a dummy variable (D_ToMay). This dummy variable has the formula:

$$D\_ToMay_t = \begin{cases} 1, \; if the\ trading\ day\ t\ belongs\ to\ the\ ToMay \\ \qquad\qquad time\ interval \\ 0, \; otherwise \end{cases}$$

The OLS models are defined by the equation:

$$r_{j,t} = \mu_0 + \mu_1 \times D\_ToMay_t + \sum_{i=1}^{n} \xi_i \times r_{j,t-i} + \varepsilon_t \qquad (2)$$

where:

- μ_0 is a coefficient that expresses the average returns from the R_ToMay time interval;
- μ_1 is a coefficient associated to the dummy variable D_ToMay, that reflects the difference between the average of returns that occur in the two time intervals: ToMay and R_ToMay;

- ξ_i is a coefficient associated to the i lagged value of the dependent variable;
- n is the number of the lagged value of $r_{j,t}$, chosen by Akaike (1974) Information Criterion;
- ε_t is the error term that is supposed to follow a normal distribution with the zero-mean and a constant variance.

We investigate the the homoscedasticity of the error term by employing Breusch - Pagan (1979) test.

Along with OLS models we also employ GARCH(1,1) models (Engle, 1982; Bollerslev, 1986). These models contain two equations, the first one being similar with equation (2). The second equation is associated to the variance of the error term (h_t) which is allowed to be variable:

$$h_t = \lambda + \alpha_1 \times \varepsilon_{t-1}^2 + \beta_1 \times h_{t-1} \qquad (3)$$

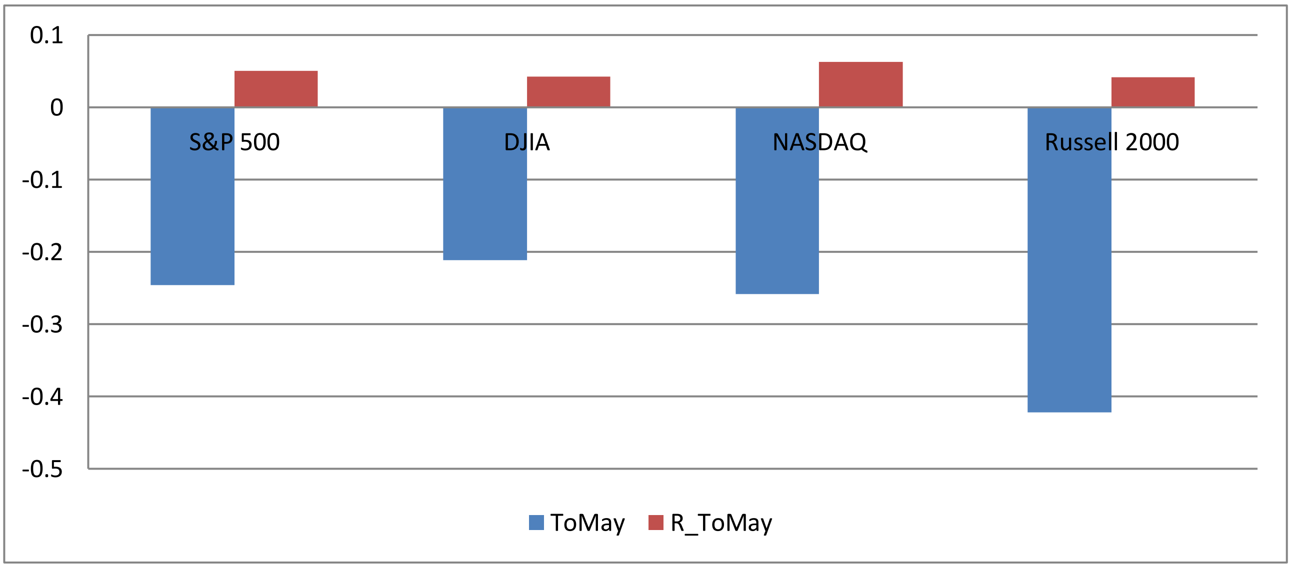
in which:

- λ is a constant term;
- α_1 is a coefficient associated to the lagged squared values of the error term;
- β_1 is a coefficient associated to the lagged variance.

3. EMPIRICAL RESULTS

The average returns for the two time intervals are presented in Fig. 1. For all four indexes we found negative values in ToMay and positive values in R_ToMay.

Fig. 1. Average returns in the two time intervals



Tab. 3 displays the results of OLS models. For all four indexes we obtained significant negative values of the μ_1 coefficients. The Breusch-Pagan tests indicate the presence of heteroskedasticity.

Tab. 3. Coefficients of OLS models

Index	S&P 500	DJIA	NASDAQ	Russell 2000

μ_0	0.0552*** (0.0178)	0.0464*** (0.0170)	0.0682*** (0.0210)	0.0446* (0.0233)
μ_1	-0.2998** (0.1240)	-0.2547** (0.1189)	-0.3232** (0.1467)	-0.4780*** (0.1625)
ξ_1	-0.1145*** (0.0159)	-0.1129*** (0.0159)	-0.0942*** (0.0159)	-0.0873*** (0.0159)
Breusch-Pagan test for heteroskedasticity	183.620***	117.265***	86.108***	42.055***

Notes: Standard errors are within parentheses; ***, ** and * mean significant at 0.01, 0.05 and 0.1 levels, respectively.

The GARCH(1,1) models provided, again, significant negative values of the μ_1 coefficients (Tab. 4).

Tab. 4. Coefficients of GARCH(1,1) models

Index	**S&P 500**	**DJIA**	**NASDAQ**	**Russell 2000**
μ_0	0.0880*** (0.0122)	0.0740*** (0.0116)	0.1024*** (0.0154)	0.0633*** (0.0178)
μ_1	-0.2141** (0.0835)	-0.1764** (0.0826)	-0.2478** (0.1137)	-0.3538*** (0.1250)
ξ_1	-0.0486*** (0.0178)	x	-0.0377** (0.0173)	x
λ	0.0366*** (0.0047)	0.0361*** (0.0048)	0.0446*** (0.0065)	0.0492*** (0.0095)
α_1	0.1648*** (0.0143)	0.1671*** (0.0147)	0.1298*** (0.0119)	0.1081*** (0.0116)
β_1	0.8055*** (0.0145)	0.7987*** (0.0154)	0.8435*** (0.0129)	0.8663*** (0.0142)

Notes: Standard errors are within parentheses; *** and ** mean significant at 0.01 and 0.05 levels, respectively.

4. CONCLUSIONS

The results of this investigation indicate, for all four indexes, abnormal low returns in the ToMay time interval. This Reverse TOM Effect in May could be explained by the impact of selling stocks in the framework of Halloween strategies. These transactions anihilated the influence of the circumstance that could generate the classical TOM Effect.

From the perspective of dispute between Efficient Markets Hypothesis and Behavioral Finance it is important the persistence in time of this form of seasonality. One of the main Efficient Markets Hypothesis' principles proclaimed that investors couldn't systematically outperform the financial markets by using knowledge about the characteristics of returns' past evolutions (e.g. Alexander, 1961; Levy, 1967; Fama, 1970). From the Behavioral Finance's perspective, any form of seasonality that could be exploited in successful investment strategies could be used as an argument against the Efficient Markets Hypothesis (e.g. Thaler, 1987; Dimson and Mussavian, 1998; Schwert, 2002; Patel and Sewell, 2015; Keloharju et al., 2016). However, the exploitation of a form of seasonality not persistent in time could be very complex (e.g. Dimson and Marsh, 1999; Marquering et al., 2006).

Many forms of seasonality experienced changes when capital markets passed from turbulent to quieter times. The period of this investigation was complex, with many extraordinary events and processes (recovery from the global financial crisis and from the Great Recession, annexation of Crimea by the Russian Federation, COVID-19 pandemic, changes in Federal Reserve's monetary policy, Russian invasion of Ukraine, global energy crisis, Gaza-War, Iran-Israel war, threats of the trade wars, etc.). Such evolutions had a significant impact on the United States capital market (e.g. Baker et al., 2020; Egger and Zhu, 2020; Wei and Han, 2021; Boungou and Yatié, 2022; Cortes et al., 2022; D'Amico and King, 2023; Chowdhury and Khan, 2024; Oh and Kim, 2024; Pandey, 2025). It is hard to anticipate if the abnormal low returns from the ToMay time interval would persist in quieter times.

This investigation about TOM effect in May could be extended to other financial markets.

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