



The Returns of Magnificent Seven Stocks in the First Days of Purchase Transactions Associated to the Halloween Strategies

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ARTICLE INFO

Article history:
Received June 30, 2025
Accepted July 28, 2025
Available online September 2025
JEL Classification
G40, G10, G14

Keywords:
Magnificent Seven Stocks,
seasonality, Halloween strategies

ABSTRACT

A Halloween strategy involves the purchasing of stocks in autumn. Such transactions could increase the stock prices in the first part of November. This paper approaches the behavior of so-called Magnificent Seven Stocks in the first part of November for the period from January 2016 to January 2025. We identified, in the case of five companies, high abnormal returns for the 4th to 8th November time interval.

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1. Introduction

In the last years, investors from United States (US) capital market paid an increasing attention to some stocks from the technology sector known as "the Magnificent Seven": Apple (AAPL), Alphabet (GOOGL), Amazon (AMZN), Meta Platforms (META), Microsoft (MSFT), Nvidia (NVDA) and Tesla (TSLA). Their high average returns made the Magnificent Seven stocks preferred by large categories of investors despite the substantial volatility. In these circumstances, the study of Magnificent Seven stocks' evolution could provide useful information to study some aspects of US capital market, such as the seasonality (Dumitriu & Stefanescu, 2024).

There are investors that use to take into consideration the seasonality of capital markets when they decide about buying or selling stocks. Such decisions defy the Efficient Markets Hypothesis' principles that proclaimed that investors couldn't systematically outperform the financial markets, by using the knowledge about the characteristics of returns past evolutions (Alexander, 1961; Levy, 1967; Fama, 1970). The followers of Behavioral Finance included many forms of capital markets seasonality in the category of anomalies (calendar anomalies) associated to Efficient Markets Hypothesis (Rozeff & Kinney Jr, 1976; Jacobs & Levy, 1988; Lakonishok & Smidt, 1988; Agrawal & Tandon, 1994).

In this paper we approach the impact of purchase transactions, associated to the Halloween strategies, on the seasonality of Magnificent Seven stocks returns. A Halloween strategy is linked to the "Sell in May Effect", a calendar anomaly that refers to a significant decline of stock prices, that is supposed to occur between May and October (Bouman & Jacobsen, 2002).

The investors could exploit this pattern in a timing strategy: they purchase stocks in autumn and they sell them in spring (Swinkels & Van Vliet, 2012; Andrade et al., 2013; Afik & Lahav, 2015; Carrazedo et al., 2016; Lloyd et al., 2017; Dzhabarov et al., 2020; Kenourgios & Samios, 2021; Magnusson, 2021; Polat, 2022; Dolvin & Foltice, 2024; Abukari et al., 2024).

A large part of the purchasing transactions could be focused during the first part of November, causing a significant increase of the stocks' prices in this time interval. A previous investigation identified abnormal returns, for two periods (January 1995 - December 2006 and January 2016 - December 2024), in the case of two time intervals: 1st to 9th November and 4th to 8th November (Stefanescu & Dumitriu, 2025).

Along with the purchasing transactions associated to the Halloween strategies, there are other circumstances that could influence the returns from the first part of November. Among them there are the factors linked to the so-called intra-month calendar anomalies (turn-of-the-month effect, half-month effect, time-of-the-month effect, etc.):

✧ transactions performed by some financial institutions in specific time intervals as parts of the tax-loss selling and the window dressing procedures etc.;

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- ✧ the standardization of various payments (salaries, bonuses, dividend etc.);
- ✧ the practice of many companies to release, in specific time intervals, information about the earnings or other results;
- ✧ the macroeconomic announcements that occur in specific time intervals etc. (Dyl, 1978; Bhabra et al., 1999; Jacobs & Levy, 1988; Brauer & Chang, 1990; Ogden, 1990; Lakonishok et al., 1991; Ogden, 1994; Gibson et al., 2000; Nofsinger, 2001; Ryan & Taffler, 2004; Gerlach, 2007; Nikkinen et al., 2007; Gosnell & Nejadmalayeri, 2010; Neuhierl et al., 2013; Chan & Gray, 2018).

Our investigation covers the period from January 2016 to January 2025. It is a period when the Magnificent Seven stocks attractiveness experienced a significant growth. We employ Ordinary Least Squares (OLS) models to identify the abnormal returns from the 1st to 9th November and 4th to 9th November time intervals. The rest of the paper is structured as follows: the chapter 2 introduces the data and it describes the methodology used in this study, the chapter 3 presents the empirical results, and the chapter 4 offers the conclusions.

2. Data and methodology

2.1. Data Description

The data set used in this paper consists of the daily closing values of Magnificent Seven Stocks, provided by Yahoo! Finance. For each of the seven stocks we calculate the logarithmic returns ($r_{i,t}$) according to 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 stock j from the days t and $t-1$, respectively.

The descriptive statistics of returns are reported in the Table 1. NVDA has the highest average and GOOG the lowest. The coefficient of variation (C.V.) experienced highest values in the case of META and TSLA. Based on the results of Jarque-Bera tests we could consider that returns of the seven stocks didn't follow normal distributions.

Table 1. Indicators of descriptive statistics for the returns of Magnificent Seven Stocks

Variable	Mean	Minimum	Maximum	C.V.	Jarque-Bera test
AAPL	0.1004	-13.7750	11.3074	17.9883	3135.52***
AMZN	0.0854	-15.1434	12.6920	24.0145	2390.37***
GOOG	0.0741	-11.7783	9.9375	24.1397	2132.95***
META	0.0827	-30.6374	20.9292	29.6463	70884.61***
MSFT	0.0936	-15.9438	13.2922	18.2310	5729.78***
NVDA	0.2194	-20.7793	25.7285	14.3645	4083.95***
TSLA	0.1414	-23.6518	19.8187	26.1194	1674.24***

Note: *** means significant at 0.01 level.

For the OLS models employed in this investigation we have to investigate the returns stationarity by employing two variants (with and without constant) of the Augmented Dickey - Fuller unit root tests (Dickey & Fuller, 1979; Dickey & Fuller, 1981). The results, displayed in the Table 2, allowed us to reject, for each stock, the null hypothesis that a unit root is present in the time series.

Table 2. Results of ADF tests

Index	Test without constant		Test with constant	
	Number of lags	Test statistic	Number of lags	Test statistic
AAPL	18	-9.5813***	18	-9.92253***
AMZN	12	-13.4328***	12	-13.6508***
GOOG	11	-14.1675***	11	-14.3878***
META	21	-8.7494***	21	-8.8774***
MSFT	14	-13.0682***	14	-13.6159***
NVDA	20	-9.0115***	20	-9.5583***
TSLA	12	-11.7508***	12	-11.8668***

Notes: The optimum number of lags was identified by Akaike (1974) Information Criterion;

*** means significant at 0.01 level.

2.2. Methodology

We use methods that are similar to those employed in Stefanescu & Dumitriu (2025). For each of the seven stocks we try to identify the abnormal return occurring in two time intervals:

- ✧ from 1st to 9th November;

✧ from 4th to 8th November.

2.2.1. Identification of the abnormal returns between 1st and 9th November

We start by defining two time intervals:

- ✧ NOV_{1,9} that contains the days between 1st and 9th November;
- ✧ R_NOV_{1,9} that includes all the days of a year excluding those from NOV_{1,9}.

To reveal the abnormal returns from NOV_{1,9} time interval we use an OLS model with a dummy variable (D_NOV_{1,9,t}) that has the formula:

$$D_NOV_{1,9,t} = \begin{cases} 1, & \text{if the trading day } t \text{ belongs to the NOV}_{1,9} \\ & \text{time interval} \\ 0, & \text{otherwise} \end{cases}$$

The OLS model is defined by the equation:

$$r_{j,t} = \mu_0 + \mu_1 \times D_NOV_{1,9,t} + \sum_{i=1}^n \xi_i \times r_{j,t-i} + \varepsilon_t \quad (2)$$

where:

- ✧ μ_0 is a coefficient that gives us the average returns during the R_NOV_{1,9} time interval;
- ✧ μ_1 is a coefficient associated to the dummy variable D_NOV_{1,9,t} that captures the difference between the average of returns from two time intervals: NOV_{1,9} and R_NOV_{1,9};
- ✧ 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 reflects the error term (the values of residuals) that is supposed to be homoscedastic; if Breusch - Pagan (1979) and White (1980) tests identified the heteroskedasticity of the error term, we apply the White (1980) methodology.

2.2.2. Identification of the abnormal returns between 4th and 8th November

We define other two time intervals:

- ✧ NOV_{4,8} that contains the days between 4th and 8th November;
- ✧ R_NOV_{4,8} that includes all the days of a year excluding those from NOV_{4,8}.

For the NOV_{4,8} time interval we associate a dummy variable (D_NOV_{4,8,t}) with the formula:

$$D_NOV_{4,8,t} = \begin{cases} 1, & \text{if the trading day } t \text{ belongs to the NOV}_{4,8} \\ & \text{time interval} \\ 0, & \text{otherwise} \end{cases}$$

We identify the abnormal returns from the NOV_{4,8} time interval by employing an OLS model with the equation:

$$r_{j,t} = v_0 + v_1 \times D_NOV_{4,8,t} + \sum_{i=1}^n \xi_i \times r_{j,t-i} + \varepsilon_t \quad (3)$$

where:

- ✧ v_0 is a coefficient that expresses the average returns from the R_NOV_{4,8} time interval;
- ✧ v_1 is a coefficient associated to the dummy variable D_NOV_{4,8,t} that gives us the difference between the average of returns from the two time intervals: NOV_{4,8} and R_NOV_{4,8};
- ✧ ξ_i , n , and ε_t have the same significances as in the previous equation.

3. Empirical Results

The Table 3 reports the results of regressions associated to the NOV_{1,9} time interval. The μ_1 coefficient has a significant positive value in the case of NVDA stock, but only for a 0.1 level.

Table 3. Coefficients of the OLS models associated to the NOV_{1,9} time interval

Index	μ_0	μ_1	ξ_1	White (1980) test	Breusch-Pagan (1979) test
AAPL	0.1019*** (0.0383)	-0.0593 (0.2363)	x	0.0153	0.0592
AMZN	0.0806* (0.0431)	0.1833 (0.3580)	x	1.7105	5.9938**
GOOGL	0.0862** (0.0370)	0.2434 (0.2547)	-0.0530** (0.0243)	83.3032***	3.9177
META	0.0776 (0.0520)	0.1937 (0.3206)	x	0.0423	0.6172

Index	μ_0	μ_1	ξ_1	White (1980) test	Breusch-Pagan (1979) test
MSFT	0.0962*** (0.0338)	0.3162 (0.1940)	-0.0907*** (0.0242)	368.493***	25.1379***
NVDA	0.2125*** (0.0662)	0.7523* (0.3838)	-0.0677*** (0.0244)	45.3347***	40.2475***
TSLA	0.1442* (0.0783)	-0.1060 (0.4834)	x	0.3016	0.9340

Notes: Standard errors are within parentheses; *** and ** mean significant at 0.01 and 0.05 levels, respectively; the standard errors and p-values were corrected by the White (1980) methodology when residuals displayed heteroskedasticity.

The results of OLS models associated to the $NOV_{4.8}$ time interval are displayed in the Table 4. We obtained significant value of the v_1 coefficient, under a 0.05 level, for five companies (AAPL, AMZN, GOOG, MSFT and NVDA). We also obtained a significant value of the v_1 coefficient in the case of META, but only for a 0.1 level.

Table 4. Coefficients of the OLS models associated to the $NOV_{4.8}$ time interval

Index	v_0	v_1	ξ_1	White (1980) test	Breusch-Pagan (1979) test
AAPL	0.0934** (0.0382)	0.4953** (0.2038)	x	1.01541	3.9263**
AMZN	0.0737* (0.0432)	0.8356** (0.3648)	x	0.01047	0.0367
GOOG	0.0808** (0.0366)	0.8774** (0.3418)	-0.0508** (0.0246)	79.1859***	4.2127
META	0.0773 (0.0518)	0.8141* (0.4300)	-0.0520** (0.0212)	1.2962	4.6494*
MSFT	0.0927*** (0.0335)	0.8950*** (0.3066)	-0.0951*** (0.0242)	365.912***	26.5016***
NVDA	0.2119*** (0.0656)	1.5065** (0.6152)	-0.0698*** (0.0244)	45.7656***	39.9902***
TSLA	0.1328* (0.0779)	0.6162 (0.6577)	x	0.0587	0.1813

Notes: Standard errors are within parentheses; *** and ** mean significant at 0.01 and 0.05 levels, respectively; the standard errors and p-values were corrected by the White (1980) methodology when residuals displayed heteroskedasticity.

4. Conclusions

The results of OLS models indicated that five of the Magnificent Seven' Stocks displayed high abnormal returns in the $NOV_{4.8}$ time interval. For two stocks with the highest volatility, META and TSLA, we didn't identify abnormal returns. The increase of prices during the $NOV_{4.8}$ time interval could be explained by the impact of purchase transactions associated to the Halloween strategies. However, the circumstances that generate the intra-month calendar anomalies could also play a major role.

We found no significant values of the μ_1 coefficient, for less than 0.05 level, in the case of $NOV_{1.9}$ time interval. Such findings are in accordance with the results of Stefanescu & Dumitriu (2025) in the case of NASDAQ Composite, an index linked to the technology sector. It is possible that some investors avoided the complex time interval November 1st – November 3rd, when the news about macroeconomic indicators or companies' results could increase the stock prices volatility.

The investigation about the Halloween strategies impact on the stocks' returns could be extended to other forms of seasonality.

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