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The Returns of US Capital Market in the First Days of Purchase Transactions Associated to the Halloween Strategies

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A R T I C L E I N F O

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A B S T R A C T

The acquisitions of stocks implied by the Halloween Strategy could cause abnormal high returns in the first part of November. This paper approaches the behavior of the returns from United States capital markets in two time intervals: the first one from 1st to 9th November and second one from 4th to 8th November. Our investigation uses four maor indexes and it covers three periods: January 1995 - December 2006, January 2007 - December 2015 and January 2016 - December 2024. We found abnormal high returns in the two time intervals for the first and third periods.

1. Introduction

Among the best known trading rules is the one based on the old saying „Sell in May and go away". For the European financial press, this proverb is continued with the advice that investors should buy back in September or, in a more precise version, on St. Leger Day (apud Bouman & Jacobsen, 2002). The reason of this recommendation is the decline of stock returns that usually occurs between May and September. For the United States (US) capital market, O'Higgins & Downes (1990) considered that a bear market started in October 31 and it ended in April 30.

An investigation of Bouman & Jacobsen (2002) on the stock markets from 37 countries identified, for 36 of them, the "Sell in May (Halloween)" Effect (a form of seasonality consisting in returns that were significantly lower during the May - October time interval than during the remainder of the year). In their opinion, this calendar anomaly is persistent in time. Other studies documented the presence of the "Sell in May" Effect for different periods and several periods (Jacobsen et al., 2005; Jacobsen & Visaltanachoti, 2009; Haggard & Witte, 2010; Swagerman & Novakovic, 2010; Andrade et al., 2013; Kochman & Bray, 2017; Degenhardt & Auer, 2018; Zhang & Jacobsen, 2021; Jain, 2023). There are, however, papers that contested the Sell in May Effect or that considered that form of seasonality weakened after it had been revealed (Maberly & Pierce, 2004; Lucey & Zhao, 2008; Dichtl & Drobetz 2015; Fuller et al., 2017).

The knowledge about the high returns from the time interval November - April could be exploited in a market timing investment strategy (Halloween strategy) which consists in purchasing stocks in November or in the following months and selling them in April or May (Bouman & Jacobsen, 2002; Swinkels & Van Vliet, 2012; Carrazedo et al., 2016; Lloyd et al., 2017; Kenourgios & Samios, 2021; Polat, 2022). Such transactions could generate abnormal returns on the stock markets.

This paper approaches the impact of purchase transactions, associated to the Halloween strategies, on the US capital market. We could consider that most of such transactions are made in the first part of November. A previous investigation identified abnormal high returns in a time interval from 1st to 8th November during two periods: January 2007 - December 2014 and January 2015 - December 2023 (Stefanescu & Dumitriu, 2024). We took into consideration two time intervals: the first one from 1st to 9th November and the second one from 4th to 9th November. Our investigation covers three periods:

- a relative quiet period, from January 1995 to December 2006;
- a quite turbulent period, from January 2007 to December 2015, when the Global Financial Crisis, the Big Recession and the European Debt Crisis generated pessimism among investors;
- the third period, from January 2016 to December 2024, when several events (COVID-19 pandemic, the unconventional monetary policies, Russian invasion of Ukraine, global energy crisis, the 2023 Hamas-

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led attack on Israel, the 2024 US presidential election, etc.) caused complex evolutions of the financial markets.

The rest of this paper is organized as it follows: the second part provides a description of data and methodology employed to investigate the presence of abnormal returns during the two time intervals, the third part presents the empirical results, and the fourth part concludes.

3. Data and methodology

3.1. Data Description

The data used in this investigation, about the impact of the Halloween strategies on US capital market, consisted in 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. Those values, which were provided by Yahoo! Finance, covered the three periods mentioned before. For each index we established a daily series of log returns computed by 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.

The Table 1 reports the descriptive statistics of returns. For all four indexes, the lowest averages occurred in the period January 2007 - December 2015. The second and third periods were characterized by a high volatility. The values of Jarque-Bera tests suggest that returns of the four indexes didn't follow a normal distribution.

Table 1. Descriptive statistics of the returns

Index	S&P 500	DJIA	NASDAQ	Russell 2000
First subsample: January 1995 - December 2006				
Mean	0.037	0.039	0.039	0.038
Median	0.061	0.051	0.132	0.107
Minimum	-7.113	-7.454	-10.168	-7.533
Maximum	5.574	6.155	13.255	5.678
Std. Dev.	1.079	1.054	1.704	1.188
IQ range	1.133	1.114	1.626	1.288
Jarque-Bera test	1603.5***	2588.7***	2599.8***	603.5***
Second subsample: January 2007 - December 2015				
Mean	0.016	0.015	0.032	0.016
Median	0.069	0.050	0.100	0.097
Minimum	-9.470	-8.201	-9.588	-12.614
Maximum	10.957	10.508	11.159	8.861
Std. Dev.	1.364	1.249	1.439	1.717
IQ range	1.091	1.017	1.270	1.658
Jarque-Bera test	8581.4***	8585.0***	4400.7***	2575.3***
Third subsample: January 2016 - December 2024				
Mean	0.047	0.039	0.060	0.030
Median	0.071	0.073	0.111	0.082
Minimum	-12.765	-13.842	-13.149	-15.399
Maximum	8.968	10.764	8.935	8.976
Std. Dev.	1.142	1.123	1.377	1.489
IQ range	0.942	0.906	1.274	1.538
Jarque-Bera test	25729.6***	54099.3***	6345.6***	12075.7***

Note: *** means significant at 0.01 level.

We investigate the stationarity of returns by employing two variants of the Augmented Dickey – Fuller unit root tests: with and without constant (Dickey & Fuller, 1979; Dickey & Fuller, 1981). For all four indexes and for all three sub-samples the null hypothesis of unit root was rejected (Table 2).

Table 2. Results of ADF tests

Index	Test without constant		Test with constant	
	Number of lags	Test statistic	Number of lags	Test statistic
First subsample: January 1995 - December 2006				
S&P 500	11	-16.046***	11	-16.194***
DJIA	8	-18.859***	12	-18.997***
NASDAQ	12	-13.612***	12	-13.660***

Russell 2000	15	-12.734***	15	-12.837***
Second subsample: January 2007 - December 2015				
S&P 500	11	-13.654***	11	-13.669***
DJIA	12	-12.714***	12	-12.729***
NASDAQ	16	-11.112***	16	-11.175***
Russell 2000	11	-13.395***	11	-13.403***
Third subsample: January 2016 - October 2024				
S&P 500	8	-14.744***	8	-14.914***
DJIA	8	-14.833***	8	-14.954***
NASDAQ	11	-13.372***	11	-13.608***
Russell 2000	11	-13.171***	11	-13.221***

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

2.2. Methodology

We study the behavior of returns from the two time intervals mentioned before:
- from 1st to 9th November;
- from 4th to 9th November.

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

We use two time intervals:
- NOV_{1_9} that is composed by 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}.

Corresponding to NOV_{1_9} time interval, we define a dummy variable ($D\_NOV_{1\_9,t}$) with the formula:

$$D\_NOV_{1\_9,t} = \begin{cases} 1, & if the\ trading\ day\ t\ belongs\ to\ the\ NOV_{1\_9}\ time\ interval \\ 0, & otherwise \end{cases}$$

In our attempt to identify the abnormal returns from the NOV_{1_9} time interval, we employ an OLS model with 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 reflects 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 expresses the difference between the average of returns from the 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 expresses 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 use a methodology that is quite similar to the previous one. The two time intervals employed are:
- NOV_{4_8} that is composed by 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 first time interval we associate a dummy variable ($D\_NOV_{4\_8,t}$) with the formula:

$$D\_NOV_{4\_8,t} = \begin{cases} 1, & if the\ trading\ day\ t\ belongs\ to\ the\ NOV_{4\_8}\ time\ interval \\ 0, & otherwise \end{cases}$$

The OLS model has the equation:

$$r_{j,t} = \nu_0 + \nu_1 \times D\_NOV_{4\_8,t} + \sum_{i=1}^{n} \xi_i \times r_{j,t-i} + \varepsilon_t \quad (3)$$

where:
- ν_0 is a coefficient that reflects the average returns during the $R\_NOV_{4\_8}$ time interval;

- ν_1 is a coefficient associated to the dummy variable $D\_NOV_{1\_9,t}$ that expresses 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 previous equation.

4. Empirical Results

3.1. Results for the first subsample

The Table 3 gives us the results of the regressions associated to the NOV_{1_9} time interval. We obtained, for all four indexes, significant positive values of the μ_1 coefficient.

Table 3. Coefficients of OLS models associated to the NOV_{1_9} time interval in the case of first subsample

Index	S&P 500	DJIA	NASDAQ	Russell 2000
μ_0	0.03190 (0.0120)	0.0330* (0.0195)	0.0243 (0.0299)	0.0305 (0.0213)
μ_1	0.2123** (0.1007)	0.2342** (0.0993)	0.3697*** (0.1273)	0.2719** (0.1183)
ξ_1	x	x	0.0477** (0.0220)	0.0741*** (0.0215)
White's test for heteroskedasticity	2.625	1.973	212.886***	118.171***
Breusch-Pagan test for heteroskedasticity	7.307***	6.422**	171.374***	93.356***

Notes: Standard errors are within parentheses; ***, ** and * mean significant at 0.01, 0.05 and 0.1 levels, respectively; the standard errors and p-values were corrected by the White (1980) methodology.

For the regressions associated to the NOV_{4_8} time interval, we found a significant value of the ν_1 coefficient, under a 0.05 level, in the case of DJIA index (Table 4). We also obtained a significant value of the ν_1 coefficient in the case of S&P 500 index, but only for a 0.1 level.

Table 4. Coefficients of OLS models associated to the NOV_{4_8} time interval in the case of first subsample

Index	S&P 500	DJIA	NASDAQ	Russell 2000
ν_0	0.0342* (0.0198)	0.0348* (0.0193)	0.03144 (0.0297)	0.0361* (0.0213)
ν_1	0.2152* (0.1284)	0.2957** (0.1300)	0.1842 (0.2023)	0.1136 (0.1420)
ξ_1	x	x	0.0495** (0.0220)	0.0762*** (0.0214)
White's test for heteroskedasticity	1.569	1.374	211.646***	118.390***
Breusch-Pagan test for heteroskedasticity	4.369**	4.478**	167.877***	94.731***

Notes: Standard errors are within parentheses; ***, ** and * mean significant at 0.01, 0.05 and 0.1 levels, respectively; the standard errors and p-values were corrected by the White (1980) methodology.

3.2. Results for the second subsample

The results of the regressions associated to the NOV_{1_9} time interval are reported in the Table 5. We found no significant value of the μ_1 coefficient.

Table 5. Coefficients of OLS models associated to the NOV_{1_9} time interval in the case of second subsample

Index	S&P 500	DJIA	NASDAQ	Russell 2000
μ_0	0.0120 (0.0273)	0.0137 (0.0249)	0.0371 (0.0304)	0.0206 (0.0366)
μ_1	-0.0607 (0.2196)	-0.0470 (0.1909)	-0.2049 (0.2456)	-0.1786 (0.2324)
ξ_1	-0.0701*** (0.2196)	-0.0827*** (0.0250)	x	x
White's test for heteroskedasticity	95.576***	102.368***	0.915	0.350
Breusch-Pagan test for heteroskedasticity	173.948***	196.011***	4.020**	1.256

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.

For the OLS models associated to the NOV_{4_8} time interval, the results indicate that values of the ν_1 coefficient are not significant (Table 6).

Table 6. Coefficients of OLS models associated to the NOV_{4_8} time interval in the case of second subsample

Index	S&P 500	DJIA	NASDAQ	Russell 2000
ν_0	0.0106 (0.0272)	0.0122 (0.0249)	0.0355 (0.03043)	0.0184 (0.0364)
ν_1	0.0085 (0.2826)	0.0417 (0.2302)	-0.2375 (0.2618)	-0.1540 (0.3012)
ξ_1	-0.0708*** (0.0253)	-0.0840*** (0.0250)	x	x
White's test for heteroskedasticity	95.741***	102.736***	1.039	0.053
Breusch-Pagan test for heteroskedasticity	176.999***	199.805***	4.568**	0.188

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.

3.3. Results for the third subsample

The Table 7 displays the results of OLS models associated to the NOV_{1_9} time interval. We obtained significant positive values of the μ_1 coefficient, under a 0.05 level, for three indexes (S&P 500, DJIA and Russell 2000). For the NASDAQ index we also found a significant value of the ν_1 coefficient, but only for a 0.1 level.

Table 7. Coefficients of OLS models associated to the NOV_{1_9} time interval in the case of third subsample

Index	S&P 500	DJIA	NASDAQ	Russell 2000
μ_0	0.0450** (0.0216)	0.0285 (0.0238)	0.0660** (0.0274)	0.0181 (0.0316)
μ_1	0.3419** (0.1506)	0.4133*** (0.1467)	0.3214* (0.1840)	0.4424** (0.1947)
ξ_1	-0.0542** (0.0246)	x	-0.0652*** (0.0246)	x
White's test for heteroskedasticity	357.282***	0.159	295.340***	0.044
Breusch-Pagan test for heteroskedasticity	80.364***	2.071	19.336***	0.288

Notes: Standard errors are within parentheses; ***, ** and * mean significant at 0.01, 0.05 and 0.1 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 presented in the Table 8. For three indexes (S&P 500, DJIA and NASDAQ) the values of ν_1 coefficient are, under a 0.05 level, significantly positive. We also obtained a significant value of the ν_1 coefficient in the case of Russell 2000, but only for a 0.1 level.

Table 8. Coefficients of OLS models associated to the NOV_{4_8} time interval in the case of third subsample

Index	S&P 500	DJIA	NASDAQ	Russell 2000
ν_0	0.05061** (0.0215)	0.0314 (0.0237)	0.0643** (0.0272)	0.0232 (0.0315)
ν_1	0.5842*** (0.1588)	0.5655*** (0.1996)	0.6944*** (0.2177)	0.4686* (0.2650)
ξ_1	-0.0539** (0.0245)	x	-0.0643*** (0.0246)	x
White's test for heteroskedasticity	355.952***	0.216	293.916***	0.114
Breusch-Pagan test for heteroskedasticity	81.398***	2.810*	20.878***	0.753

Notes: Standard errors are within parentheses; ***, ** and * mean significant at 0.01, 0.05 and 0.1 levels, respectively; the standard errors and p-values were corrected by the White (1980) methodology when residuals displayed heteroskedasticity.

4. Conclusions

The results of this investigation could be interpreted as evidence of a significant impact of the Halloween strategies on US capital market. However, it can be rejected the hypothesis that abnormal high returns from the first part of November were caused by other factors, especially those specific to intra-month calendar anomalies: news announcements regarding companies' results or macroeconomic indicators scheduled to be released in that time interval, the standardization of various payments, the tax-loss selling and the window dressing practices, 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; Neuhierl et al., 2013).

The empirical results also suggested that stock returns from the two time intervals were sensitive to changes in the context that occurred during the three periods of investigation. Between January 1995 and December 2006, when the financial markets experienced a relatively quiet context, all four indexes displayed abnormal high returns in the NOV_{1_9} time interval. In the same period, we found abnormal high returns in the NOV_{4_8} time interval only for the Dow Jones Industrial Average index.

The Global Financial Crisis, the Big Recession and the European Debt Crisis generated pessimism among investors between January 2007 and December 2015 (Bosworth & Flaaen, 2009; Hurd & Rohwedder, 2010; Wyplosz, 2010; Garcia, 2013; Ameur et al., 2024). In this context, we found no abnormal return for the two time intervals. It was documented that many forms of seasonality weakened or disappeared in periods of crisis (Holden et al., 2005; Hui, 2005; Lu et al., 2015; Vasileiou & Samitas, 2015).

Between January 2016 and December 2024 there were events, such as the changes in Federal Reserve's monetary policy, the COVID 19 pandemic or the Ukraine–Russia war, that generated complex evolutions of the US capital market (Baker et al., 2020; Benmelech & Tzur-Ilan, 2020; Wei & Han, 2021; Boungou & Yatié, 2022; Cortes et al., 2022; D'Amico & King, 2023; Chowdhury & Khan, 2024). In this period two indexes (Standard & Poor's 500 and Dow Jones Industrial Average) had abnormal high returns for both time intervals. The Russell 2000 index, which reflects the small companies' performances, displayed abnormal high returns for NOV_{1_9} but not for NOV_{4_8}. This fact could be explained by the impact of the firm size on the stock returns' seasonality (Keim, 1983; Schwert, 1983; Chen & Jindra, 2010). In the case of NASDAQ Composite index we found abnormal high returns for NOV_{4_8} but not for NOV_{1_9}. In the last years, the evolution of this index was influenced by the major transformations from the technology sector (Drabik, 2021; Teti & Maroni, 2021; Kumar, 2021; Demmler & Fernández, 2024). Some investors could hesitate to purchase stocks in the first days of a month when the prices could be high because of the TOM Effect and when the uncertainty about monetary policy could be significant.

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