International Journal of
Financial Studies

Article

A Closer Look at the Halloween Effect: The Case of the Dow Jones Industrial Average

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Received: 22 December 2017; Accepted: 9 April 2018; Published: 12 April 2018

Abstract: The Halloween effect is one of the most famous calendar anomalies. It is based on the observation that stock returns tend to perform much better over the winter half of the year (November–April) than over the summer half of the year (May–October). The vast majority of studies that investigated the Halloween effect over the recent decades focused only on stock indices. This means that they evaluated whether a stock index follows the Halloween effect pattern, but they omitted digging a little deeper and analyze the Halloween effect on the individual stocks level. This paper investigates to what extent the blue-chips stocks included in the Dow Jones Industrial Average are affected by the Halloween effect and whether the Halloween effect is widespread or the behavior of the whole index is driven by only a handful of stocks that are strongly affected by the Halloween effect. The results show that, although the strength of the Halloween effect varies quite rapidly from stock to stock, the vast majority of analyzed stocks experienced a notably higher average winter period than summer period returns over the 1980–2017 period. Moreover, in 18 out of 35 cases, the Halloween effect was statistically significant.

Keywords: Halloween effect; calendar anomaly; stock market; Dow Jones Industrial Average

JEL Classification: G10; G11; G15

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1. Introduction

Various calendar anomalies have been the center of attention of many researchers in recent decades. The studies were usually motivated by theoretical as well as practical targets. From the theoretical point of view, the existence of calendar anomalies proves the original efficient markets theory (Fama 1965) wrong. According to Fama, the share price always reflects all of the relevant information. As a result, the technical and fundamental analyses are unable to predict the future share price movements. However, the existence of a calendar anomaly means that the price development can be predicted to some extent. From the practical point of view, it is possible to assume that, in some cases, a calendar anomaly may be used as part of an investment strategy that is able to generate abnormal returns.

One of the oldest and most famous calendar anomalies is the Halloween effect. The Halloween effect is based on the tendency of stock markets to perform better during the winter half of a year that lasts from November to April than during the summer half of a year lasting from May to October. The Halloween effect got its name due to the fact that the more positive half of the year starts around Halloween.

The Halloween effect is not a new phenomenon. According to Bouman and Jacobsen (2002), it can be tracked back to 1694 on the British stock market. They also discovered the Halloween effect on share markets in 35 out of 37 investigated countries. In 20 cases, the difference between the winter period and summer period returns was statistically significant. A similar study was also conducted by Andrade et al. (2013), who investigated the same group of stock markets with newer data. They confirmed the results of Bouman and Jacobsen and concluded that the average difference between the winter and summer period returns tends to be around 10 percentage points. On the other hand, the results of Bouman and Jacobsen were criticised by Maberly and Pierce (2004), who claimed that the Halloween effect was caused mainly by the stock market crash of 1987 and by the 1998 bankruptcy of the Long-Term Capital Management investment fund. They adjusted the data for these two events and they concluded that there was no statistically significant Halloween effect on the U.S. stock market. The study of Maberly and Pierce was criticised by Witte (2010). Witte criticised the elimination of the 1987 and 1998 events. He used several methods to prove that there was a statistically significant Halloween effect on the U.S. stock market. According to Lloyd et al. (2017), the Halloween effect hasn't disappeared even after the 2008 global financial crisis. During the 2007–2015 period, they discovered the Halloween effect on stock markets in 34 out of 35 investigated countries. However, it was statistically significant only in six countries.

Some of the authors focused on the sectoral differences in the Halloween effect. Jacobsen and Visaltanachoti (2009) investigated the U.S. stock market over the 1926–2009 period. They concluded that the Halloween effect affected stocks of companies from 48 out of the 49 investigated industries. In the majority of industries, the differences between the winter period and summer period returns were statistically significant. However, they also concluded that there are notable differences between individual industries. Dzhabarov and Ziemba (2010) compared the behaviour of the large-cap stocks represented by the S&P 500 stock index and the small-cap stocks represented by the Russell 2000 stock index and they discovered that the Halloween effect was stronger for the small-cap stocks.

Several authors focused also on the presence of the Halloween effect on less developed stock markets. Lean (2011) discovered that the Halloween effect can be found on the stock markets of southeast Asia, namely on the Malaysian, Chinese, Indian, Japanese and Singaporean stock markets. Guo et al. (2014) discovered a significant Halloween effect on the Chinese stock market over the 1997–2013 time period. Arendas and Chovancova (2016) concluded that the Halloween effect also impacts the stock markets in the Central and Eastern Europe (CEE) region. According to them, the Halloween effect can be found on stock markets of the majority of the 12 investigated CEE countries; however, it was statistically significant only in the case of Poland and Ukraine. An interesting conclusion came from Swagerman and Novakovic (2010), who found out that the Halloween effect is stronger on the developed rather than on the developing stock markets.

Some of the recent studies focused also on the presence of the Halloween effect in other segments of the financial markets. Zaremba and Schabek (2017) investigated the presence of the Halloween effect on the government bonds markets in 25 countries, over the 1992–2016 time period. They found out that the bond returns as well as the factor premia were unaffected by the Halloween effect. Arendas (2017) concluded that the Halloween effect can be found in agricultural commodities markets. Fifteen out of the 20 investigated agricultural commodities recorded a higher average winter period than summer period returns and, in 10 cases, the differences were statistically significant at $\alpha = 0.05$.

Various authors investigated the possibility of utilization of the Halloween effect in investment strategies. While Dichtl and Drobetz (2014) concluded that an investment strategy based on the Halloween effect is unable to generate notably higher returns compared to a simple buy and hold strategy, Swagerman and Novakovic (2010); Haggard and Witte (2010); and Andrade et al. (2013) concluded that a strategy of switching between the stock investment during the winter periods and t-bills during the summer periods is able to beat the buy and hold strategy significantly. According to Swagerman and Novakovic, the Halloween effect-based investment strategy was a better option in 19 out of 23 investigated stock markets. Lloyd et al. (2017) proposed an even more aggressive investment strategy based on shorting the stock market over the summer periods and holding a long position over the winter periods. Over the 2007–2015 time period, this strategy was able to beat the abovementioned traditional Halloween effect-based investment strategy by 3.2 percentage points and the buy and hold strategy by 4.77 percentage points per year on average. Based on the findings of Carrazedo et al. (2016), a Halloween effect-based investment strategy tends to be successful in two out of three calendar years. In addition, according to Haggard et al. (2015), a Halloween effect-based investment strategy can outperform. However, as the Halloween effect is strongly influenced by the outliers, the investors should be prepared that a series of outlier-less years when the Halloween effect-based investment strategy underperforms may also occur.

Although various aspects of the Halloween effect have been investigated over the last two decades, most of the researchers focused on the stock indices, without paying any attention to the individual companies whose stocks are included in the index. However, there are several questions that can be answered only on this micro-level. This article investigates how much the companies included in the Dow Jones Industrial Average stock index are affected by the Halloween effect. Given that various studies confirm that the Dow Jones Industrial Average follows the Halloween effect pattern and that Jacobsen and Visaltanachoti (2009) discovered the Halloween effect in 48 out of 49 industries, we assume that the majority of stocks included in the Dow Jones Industrial Average are affected by the Halloween effect. This paper should help us confirm or refute this assumption.

2. Data and Methodology

The aim of the paper is to find out whether the majority of the companies included in the Dow Jones Industrial Average stock index follow the Halloween effect pattern, or whether the behaviour of the whole stock index is driven by only a handful of companies that are extremely strongly affected by the Halloween effect.

The analysis is focused on the identification of the presence of the Halloween effect in the price performance of major stock companies that were a part of the Dow Jones Industrial Average for some time during the 1980–2017 period. As the composition of Dow Jones Industrial Average changes over time, some of the companies go bankrupt or are acquired by their peers, it is impossible to make a long-term analysis of all of the companies included in the stock index. This is why not all of the stock companies that were included in the Dow Jones Industrial Average over the 37-year time period were included in the analysis. An analyzed stock company must fit the following criteria:

1. It was included in the Dow Jones Industrial Average for some time during the 1980–2017 period.
2. The original company still exists and its shares are still publicly traded, without any interruptions.
3. Price data for at least 30 years since 1980 are available.

Out of the 57 companies included in the Dow Jones Industrial Average since 1980, only 41 still exist and are traded on a major stock exchange. The rest of them went bankrupt or were acquired by another company and delisted. For only 35 out of the 41 companies, data for at least 30 years since 1980 are available. A detailed list of the companies along with the information about which of the three criteria they failed to meet is presented in Appendix A, Table A1. The price data were provided by the Stooq database. The list of the 35 companies that meet all of the three criteria, as well as the length of the analyzed time periods, are presented in Table 1.

Table 1. Analyzed stocks.

Company	Number of Years	Time Period	Company	Number of Years	Time Period
3M	37	V. 1980–IV. 2017	Chevron	37	V. 1980–IV. 2017
AIG	32	V. 1985–IV. 2017	IBM	37	V. 1980–IV. 2017
Alcoa	37	V. 1980–IV. 2017	Intel	37	V. 1980–IV. 2017
Altria Group	37	V. 1980–IV. 2017	International Paper	37	V. 1980–IV. 2017
American Express	37	V. 1980–IV. 2017	J. P. Morgan Chase	37	V. 1980–IV. 2017
Apple	32	V. 1985–IV. 2017	Johnson & Johnson	37	V. 1980–IV. 2017
AT&T	32	V. 1985–IV. 2017	McDonald´s	37	V. 1980–IV. 2017
Bank of America	30	V. 1987–IV. 2017	Merck	37	V. 1980–IV. 2017
Boeing	37	V. 1980–IV. 2017	Microsoft	31	V. 1986–IV. 2017
Caterpillar	37	V. 1980–IV. 2017	Navistar	37	V. 1980–IV. 2017
Citigroup	37	V. 1980–IV. 2017	Pfizer	35	V. 1982–IV. 2017
Coca-Cola	37	V. 1980–IV. 2017	Procter & Gamble	37	V. 1980–IV. 2017
DuPont	37	V. 1980–IV. 2017	United Health	32	V. 1985–IV. 2017
ExxonMobil	37	V. 1980–IV. 2017	United Technologies	37	V. 1980–IV. 2017
General Electric	37	V. 1980–IV. 2017	Verizon	33	V. 1984–IV. 2017
Goodyear	37	V. 1980–IV. 2017	Wal-Mart Stores	37	V. 1980–IV. 2017
Home Depot	35	V. 1982–IV. 2017	Walt Disney	37	V. 1980–IV. 2017
Honeywell	37	V. 1980–IV. 2017	**DJIA**	**37**	**V. 1980–IV. 2017**

Source: own processing.

Two hypotheses are being tested:

Hypothesis 1. *Over the investigated time period, the majority of the analyzed stocks followed the Halloween effect pattern, i.e., the average winter period returns were higher than the average summer period returns and the percentage of Halloween effect years was higher than 50.*

Hypothesis 2. *Over the investigated time period, the Halloween effect was statistically significant for the majority of investigated stock companies.*

To investigate the presence of the Halloween effect, the whole time periods are divided into summer periods (May–October) and winter periods (November–April), and the returns for all of the summer and winter periods are calculated. If, in a given year, a particular stock was affected by the Halloween effect, the winter period return must be higher than the summer period return. If the existence of the Halloween effect is only accidental over the investigated time period, the number of years when the winter period returns were higher than the summer period returns should be approximately equal to the number of years when the winter period returns were lower than the summer period returns. In this case, the average difference between the winter period and summer period returns should also be close to 0. If the percentage of years when the Halloween effect was recorded is notably higher than 50 and the average difference between the winter period and summer period returns is notably higher than 0 percentage points, it is possible to conclude that the investigated stock is affected by the Halloween effect.

A binomial test that evaluates whether the percentage of Halloween effect years is statistically significantly higher than 50 is conducted.

In order to determine whether the Halloween effect is statistically significant, two types of statistical significance tests are performed, namely, the parametric two-sample t-test and the non-parametric Wilcoxon rank-sum test. As the parametric test is more robust for normally distributed data and the non-parametric test is more robust for non-normally distributed data, the Shapiro–Wilk test is performed in order to determine whether the individual data series have normal or non-normal distribution. The F-test is used to investigate whether the compared time series have equal variances, thus whether the two-sample t-test for equal variances or two-sample t-test for unequal variances should be used.

3. Results

As can be seen in Table 2, over the 1980–2017 time period, the vast majority of analyzed stocks experienced the Halloween effect in more than 50% of years. The most successful in this regard were Caterpillar and Walt Disney. The major machinery maker and the media company experienced the Halloween effect in 29 of 37 years, which means that the percentage of Halloween effect years equals 78.38. Another six companies (DuPont, ExxonMobil, General Electric, Honeywell, Navistar, United Technologies) experienced the Halloween effect in more than 2/3 of years. Out of the 35 companies, 29 experienced the Halloween effect in more than 50% of the years. Only AIG, Altria Group, Coca-Cola, Microsoft, Procter & Gamble and Verizon reached the percentage of Halloween effect years lower than 50. The lowest occurrence of the Halloween effect years was recorded in the case of Procter & Gamble. The consumer goods producer experienced the Halloween effect only in 14 out of 37 years analyzed. The Dow Jones Industrial Average alone experienced the Halloween effect in 28 out of 37 years (75.68% of cases). The average percentage of Halloween effect years for the whole group of analyzed stocks equals 59.57. (The summer and winter period returns descriptive statistics are presented in Appendix B, Tables A2 and A3).

Table 2. The presence of the Halloween effect (1980–2017).

	Percentage of Halloween Effect Years	Average Summer Period Returns (S)	Average Winter Period Returns (W)	Difference (W-S) (in Percentage Points)
3M	62.16	3.25%	9.56%	6.32
AIG	40.63	5.58%	4.58%	−1.00
Alcoa	64.86	−0.95%	12.06%	13.01
Altria Group	43.24	11.21%	7.23%	−3.98
American Express	59.46	2.41%	12.92%	10.51
Apple	53.13	11.87%	19.07%	7.20
AT&T	53.13	6.81%	4.36%	−2.45
Bank of America	60.00	1.32%	12.68%	11.37
Boeing	59.46	4.83%	9.62%	4.80
Caterpillar	78.38	−3.30%	17.15%	20.45
Citigroup	56.76	3.68%	7.34%	3.66
Coca-Cola	48.65	5.86%	7.69%	1.83
DuPont	67.57	0.04%	11.92%	11.89
ExxonMobil	67.57	2.31%	7.34%	5.03
General Electric	67.57	1.33%	10.75%	9.42
Goodyear	56.76	2.03%	15.80%	13.77
Home Depot	60.00	8.37%	22.61%	14.24
Honeywell	67.57	−0.48%	13.84%	14.32
Chevron	62.16	2.86%	8.08%	5.22
IBM	56.76	1.24%	7.95%	6.71
Intel	62.16	5.21%	14.73%	9.52
International Paper	70.27	0.56%	9.44%	8.88
J. P. Morgan Chase	62.16	0.41%	14.82%	14.41
Johnson & Johnson	62.16	5.74%	9.28%	3.54
McDonald´s	56.76	3.96%	12.02%	8.06
Merck	54.05	6.11%	8.02%	1.91
Microsoft	45.16	10.46%	16.91%	6.45
Navistar	72.97	−12.26%	21.48%	33.74
Pfizer	54.29	5.79%	8.21%	2.42
Procter & Gamble	37.84	8.46%	3.21%	−5.25
United Health	59.38	9.78%	19.07%	9.29
United Technologies	72.97	2.05%	13.11%	11.07
Verizon	48.48	5.49%	3.72%	−1.76
Wal-Mart Stores	62.16	8.24%	13.01%	4.77
Walt Disney	78.38	−1.23%	19.49%	20.72
DJIA	**75.68**	**1.56%**	**8.42%**	**6.85**

Source: own processing.

As can be seen, although 28 out of 35 analyzed stocks also recorded positive average returns during the summer periods, and the winter period returns tended to be significantly higher. If the average seasonal returns presented in Table 2 are averaged for the whole group of 35 companies, the summer period average equals 3.69% and the winter period average equals 11.69%. For comparison, the Dow Jones Industrial Average recorded average summer period returns of 1.56% and average winter period returns of 8.42% over the 1980–2017 period.

Table 2 also captures the average differences between the winter period and summer period returns. As can be seen, over the investigated time period, 28 out of the 35 stocks recorded higher average winter period than summer period returns. Only AIG, Altria Group, AT&T, Procter & Gamble and Verizon did better over the summer periods than over the winter periods. The Dow Jones Industrial Average recorded average winter period returns that were 6.85 percentage points higher compared to the average summer period returns. The average value for all of the 35 companies was eight percentage points in favor of the winter periods. It is also possible to see that the differences differ quite rapidly stock to stock. For example, the pharmaceutical company Merck recorded an average difference between winter period and summer period returns of only 1.91 percentage points, while Walt Disney recorded an average difference of 20.72 percentage points and Navistar recorded an average difference of 33.74 percentage points.

Based on the abovementioned results, it is possible to accept Hypothesis 1 (over the investigated time period, the majority of the analyzed stocks followed the Halloween effect pattern, i.e., the average winter period returns were higher than the average summer period returns and the percentage of Halloween effect years was higher than 50). Over the investigated time period, 28 out of the 35 analyzed stocks recorded higher average winter period than summer period returns and also recorded the Halloween effect in more than 50% of analyzed years.

Table 3 shows the results of a binomial test that evaluates whether the percentage of the Halloween effect years higher than 50 can be only a matter of chance and also the statistical significance tests that evaluate whether the differences between the summer period and winter period returns are statistically significant.

The results of the binomial test show that, in the case of 18 stocks, the occurrence of the Halloween effect is more frequent than expected by chance (in three cases (American Express, Boeing, Home Depot) at $\alpha = 0.1$, in 11 cases (3M, Alcoa, DuPont, ExxonMobil, General Electric, Honeywell, Chevron, Intel, J. P. Morgan, Johnson & Johnson, Wal-Mart Stores) at $\alpha = 0.05$ and in 4 cases (Caterpillar, International Paper, Navistar, United Technologies) at $\alpha = 0.01$). Although these results are interesting, from an investor's standpoint, the information about whether the differences between the winter period and summer period returns are statistically significant is more important.

The results of statistical significance tests include results of the parametric two-sample *t*-test and the non-parametric Wilcoxon rank sum test. The results of the more appropriate test, based on whether the analyzed data are normally distributed, are written in bold. The last column shows whether the difference between the winter period and summer period returns of a given stock is statistically significant (*—statistically significant at $\alpha = 0.1$; **—statistically significant at $\alpha = 0.05$; ***—statistically significant at $\alpha = 0.01$).

Out of the 35 analyzed stock companies, 18 recorded a statistically significant Halloween effect over the investigated time period. In one case (Bank of America), it was statistically significant at $\alpha = 0.1$, in 10 cases (3M, Alcoa, American Express, Exxon Mobil, General Electric, Goodyear, Home Depot, IBM, J. P. Morgan, McDonald's), it was statistically significant at $\alpha = 0.05$ and in seven cases (Boeing, DuPont, Honeywell, International Paper, Navistar, United Technologies, Walt Disney), it was statistically significant at $\alpha = 0.01$. For comparison, in the case of Dow Jones Industrial Average alone, the Halloween effect was statistically significant at $\alpha = 0.01$.

As 18 out of 35 analyzed stocks experienced a statistically significant Halloween effect, it is possible to also accept Hypothesis 2 (over the investigated time period, the Halloween effect was statistically significant for the majority of investigated companies).

Table 3. Statistical significance tests.

	Binomial Test (p-Value)	Two Sample t-Test (Two-Tailed p-Values)	Wilcoxon Rank Sum Test (Two-Tailed p-Values)	Statistical Significance
3M	0.04944 **	**0.02260**	0.01195	**
AIG	0.81146	0.85520	**0.41275**	
Alcoa	0.02352 **	**0.01215**	0.02938	**
Altria Group	0.74431	0.44136	**0.57769**	
American Express	0.09387 *	**0.02482**	0.04157	**
Apple	0.29831	**0.43331**	0.34727	
AT&T	0.29831	**0.45715**	0.49348	
Bank of America	0.10024	0.11191	**0.05461**	*
Boeing	0.09387 *	**0.35355**	0.23650	
Caterpillar	0.00010 ***	**0.00003**	0.00002	***
Citigroup	0.16200	**0.51407**	0.64203	
Coca-Cola	0.50000	**0.60340**	0.70114	
DuPont	0.01004 **	**0.00429**	0.00574	***
ExxonMobil	0.01004 **	**0.04335**	0.06529	**
General Electric	0.01004 **	**0.01267**	0.00613	**
Goodyear	0.16200	0.07950	**0.02488**	**
Home Depot	0.08773 *	0.06887	**0.02234**	**
Honeywell	0.01004 **	**0.00080**	0.00116	***
Chevron	0.04944 **	**0.10063**	0.13153	
IBM	0.16200	**0.06892**	0.09702	**
Intel	0.04944 **	0.15859	**0.15514**	
International Paper	0.00382 ***	0.03366	**0.00188**	***
J. P. Morgan	0.04944 **	0.00774	**0.01926**	**
Johnson & Johnson	0.04944 **	**0.26217**	0.36668	
McDonald´s	0.16200	**0.02782**	0.04050	**
Merck	0.25569	**0.64659**	0.79945	
Microsoft	0.63995	0.36918	**0.96070**	
Navistar	0.00128 ***	0.00057	**0.00020**	***
Pfizer	0.24978	0.56128	**0.48462**	
Procter & Gamble	0.90613	0.05943	**0.13153**	
United Health	0.10766	0.21726	**0.17505**	
United Technologies	0.00128 ***	**0.00474**	0.00555	***
Verizon	0.50000	**0.56109**	0.44543	
Wal-Mart Stores	0.04944 **	0.26899	**0.37827**	
Walt Disney	0.00010 ***	0.00004	**0.00004**	***
DJIA	0.00038 ***	**0.00324**	0.00821	***

Source: own processing.

4. Discussion

The results show that the Dow Jones Industrial Average followed the Halloween effect pattern over the 1980–2017 time period. It is no surprise, as multiple studies confirmed the presence of the Halloween effect on the U.S. stock market over different time periods—among the most known studies include Bouman and Jacobsen (2002); Jacobsen and Visaltanachoti (2009); Dzhabarov and Ziemba (2010); Swagerman and Novakovic (2010); and Andrade et al. (2013).

The presented results also show that the Halloween effect affects stocks of companies from different industries. The strongest Halloween effect could be seen in the case of Walt Disney (media), Navistar (transportation equipment), Caterpillar (machinery) United Technologies (aerospace and defense) and Honeywell (electrical equipment). It is in line with findings of Jacobsen and Visaltanachoti (2009) who identified the Halloween effect in 48 out of 49 investigated industries.

Importantly, the vast majority, 28 out of the 35 investigated stocks, experienced higher average winter period than summer period returns. In 18 cases, the difference was statistically significant. This finding is important, as it may have some significant practical implications. Many authors, e.g., Swagerman and Novakovic (2010); Haggard and Witte (2010); and Lloyd et al. (2017), came to a conclusion that the Halloween effect may be used as a cornerstone for some very successful investment strategies. The results presented in this paper indicate that the Halloween effect-based investment strategies should be suitable not only when investing in the financial instruments related to the major stock indices, but also when investing directly in individual stocks. This applies especially for stocks that tend to be significantly affected by the Halloween effect, i.e., they maintain a high percentage of Halloween effect years and a high positive difference between the average winter period and summer period returns. It means stocks such as Navistar that experienced the Halloween effect in 27 out of the last 37 years (or in 72.97% of cases) and the average difference between the winter period and summer period returns equaled 33.74 percentage points, or Walt Disney, which experienced the Halloween effect in 29 out of the last 37 years (or in 78.38% of cases), and the average difference between the winter period and summer period returns equaled 20.72 percentage points. These numbers are robust enough for a Halloween effect-based investment strategy to outperform the buy and hold investment strategy notably.

5. Conclusions

The analysis shows that the Halloween effect is a widespread phenomenon. The analysis of stock price behavior of 35 major U.S. stock companies that were a part of the Dow Jones Industrial Average for some time over the last 37 years shows that most of them (28 out of 35) follow the Halloween effect pattern (they experienced the Halloween effect in more than 50% of years and their average winter period returns were higher than their average summer period returns). However, it is important to note that the difference between the average winter period and the average summer period returns varies quite notably from stock to stock; moreover, it was statistically significant only in 18 out of 35 cases. Despite this observation, it is possible to conclude that the behavior of the Dow Jones Industrial Average that follows the Halloween effect pattern is not affected by only a handful of companies that are strongly affected by the Halloween effect, as the Halloween effect affects the majority of its components, whether the influence is statistically significant or not. It can be concluded that the Halloween effect-based investment strategies may be successfully used not only when investing in financial instruments that track the Dow Jones Industrial Average, as suggested by previous authors, but also when investing in individual stock companies. It is also possible to assume that the same is valid not only for the Dow Jones Industrial Average and its components, but also for other stock indices. However, further research is needed to confirm this assumption.

Acknowledgments: This paper is an outcome of the science project VEGA (1/0009/17) "Building of the capital union in Europe and its impacts on individual member countries".

Author Contributions: Peter Arendas provided the idea, constructed the hypotheses and analyzed the data. Viera Malacka and Maria Schwarzova collected and prepared the data and reviewed the literature.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Selection of the analyzed companies.

	Included in DJIA	The Original Company Still Exists	At Least 30 Years of Data Available after 1980	Note
3M	1976–2017	yes	yes	former Minnesota Mining
AIG	2004–2008	yes	yes	
Alcoa	1959–2013	yes	yes	
Altria Group	1985–2008	yes	yes	former Phillip Morris
American Brands	1932–1985	no	yes	former American Tobacco; the original company ceased to exist in 2011
American Express	1982–2017	yes	yes	
American Telephone & Telegraph	1984–2004	no	no	later renamed to AT&T; in 2005 acquired by SBC Communications that adopted its name
Apple	2015–2017	yes	yes	

Table A1. *Cont.*

	Included in DJIA	The Original Company Still Exists	At Least 30 Years of Data Available after 1980	Note
AT&T	1999–2015	yes	yes	former SBC Communications, in 2005 acquired the old AT&T and adopted its name
Bank of America	2008–2013	yes	yes	
Bethlehem Steel	1928–1997	no	no	bankrupted in 2001
Boeing	1987–2017	yes	yes	
Caterpillar	1991–2017	yes	yes	
Cisco Systems	2009–2017	yes	no	
Citigroup	1997–2009	yes	yes	former Travelers Group
Coca-Cola	1987–2017	yes	yes	
Du Pont	1935–2017	yes	yes	
Eastman Kodak	1930–2004	no	yes	the original company bankrupted in 2012, it was restructured in 2013
ExxonMobil	1928–2017	yes	yes	former Standard Oil
General Electric	1928–2017	yes	yes	
General Foods	1928–1985	no	no	acquired by Kraft in 1990
General Motors	1928–2009	no	no	the original company bankrupted in 2009
Goldman Sachs	2013–2017	yes	no	
Goodyear	1930–1999	yes	yes	
Hewlett-Packard	1997–2013	no	yes	the original company ceased to exist in 2015
Home Depot	1999–2017	yes	yes	
Honeywell	1928–2008	yes	yes	former Allied Chemicals & Dye and later Allied Signal
Chevron	2008–2017	yes	yes	
IBM	1979–2017	yes	yes	
Intel	1999–2017	yes	yes	
International Nickel (Inco)	1928–1987	no	no	acquired by Vale in 2006
International Paper	1956–2004	yes	yes	
J. P. Morgan Chase	1991–2017	yes	yes	former J.P. Morgan
Johns-Manville	1930–1982	no	no	bankrupted in 1982
Johnson & Johnson	1997–2017	yes	yes	
McDonald´s Corporation	1985–2017	yes	yes	
Merck	1979–2017	yes	yes	
Microsoft	1999–2017	yes	yes	
Navistar	1928–1991	yes	yes	former International Harvester
Nike	2013–2017	yes	no	
Owens-Illinois Glass	1959–1987	yes	no	
Pfizer	2004–2017	yes	yes	
Primerica	1928–1991	no	no	former American Can, later a part of Travelers Group; reintroduced to the stock market in 2009
Procter & Gamble	1932–2017	yes	yes	
Sears Roebuck	1928–1999	no	no	the original company acquired by Kmart in 2005; later reintroduced to the share market as Sears Holdings
Texaco	1928–1997	no	no	acquired by Chevron in 2001
The Travelers Companies	2009–2017	no	no	acquired in the 1990′s, returned to the stock market in 2005

Table A1. *Cont.*

	Included in DJIA	The Original Company Still Exists	At Least 30 Years of Data Available after 1980	Note
Union Carbide	1928–1999	no	no	since 2001 a wholly owned subsidiary of Dow Chemical Company
United Health	2012–2017	yes	yes	
United Technologies	1939–2017	yes	yes	former United Aircraft
US Steel	1928–1991	yes	no	
Verizon	2004–2017	yes	yes	
Visa	2013–2017	yes	no	
Wal-Mart Stores	1997–2017	yes	yes	
Walt Disney	1991–2017	yes	yes	
Westinghouse Electric	1928–1997	no	no	renamed to CBS corp. in 1997; acquired by Viacom in 1999—the original company ceased to exist
Woolworth	1928–1997	no	no	out of business since 1997

Source: own processing, using data of SPDJI.com and Stooq.com.

Appendix B

Table A2. Summer period returns—Descriptive statistics.

	Average	Median	Minimum	Maximum	Standard Deviation	Skewness
3M	0.03248	0.02018	−0.18715	0.36709	0.12491	0.51002
AIG	0.05577	0.07401	−0.95866	0.34135	0.23449	−2.62513
Alcoa	−0.00955	−0.01779	−0.66930	0.37694	0.22567	−0.50401
Altria Group	0.11206	0.10924	−0.25161	0.73446	0.19770	0.76290
American Express	0.02407	0.03142	−0.42735	0.38154	0.18532	−0.53084
Apple	0.11871	0.08251	−0.68467	1.03260	0.38715	0.45507
AT&T	0.06814	0.05531	−0.28874	0.33614	0.13457	−0.13524
Bank of America	0.01317	0.01223	−0.53784	0.63250	0.24732	−0.03678
Boeing	0.04826	−0.00367	−0.47252	0.71820	0.25214	0.47543
Caterpillar	−0.03300	−0.03777	−0.53134	0.54737	0.21527	0.39455
Citigroup	0.03682	0.05540	−0.45947	0.37638	0.20634	−0.58787
Coca-Cola	0.05859	0.04421	−0.24966	0.33479	0.14972	−0.03717
DuPont	0.00037	0.01116	−0.33546	0.46738	0.16131	0.11922
ExxonMobil	0.02311	0.02502	−0.19254	0.25277	0.09943	0.01481
General Electric	0.01327	0.02660	−0.40284	0.33846	0.15386	−0.34493
Goodyear	0.02028	−0.03845	−0.67639	1.36841	0.37506	1.17144
Home Depot	0.08372	0.08038	−0.38438	1.56986	0.34088	2.41611
Honeywell	−0.00479	−0.00289	−0.48739	0.44019	0.18322	−0.41929
Chevron	0.02861	0.02519	−0.21961	0.30385	0.13047	−0.13946
IBM	0.01237	0.02669	−0.26282	0.29599	0.15243	0.01774
Intel	0.05209	0.03119	−0.39528	0.79362	0.27681	0.66263
J. P. Morgan	0.00406	0.02661	−0.54354	0.38819	0.20838	−0.51008
Johnson & Johnson	0.05739	0.07027	−0.11480	0.33718	0.10691	0.27887
Microsoft	0.10460	0.08224	−0.21717	0.45650	0.16737	0.24339
Navistar	−0.12258	−0.18919	−0.58945	1.03779	0.33222	1.38814
International Paper	0.00555	−0.04490	−0.34045	0.76236	0.19072	1.82872
McDonald´s	0.03959	0.03788	−0.36233	0.46176	0.15907	0.14763
Merck	0.06113	0.07074	−0.33375	0.35909	0.17068	−0.23586
Pfizer	0.05785	0.03930	−0.24301	0.48866	0.16995	0.58775
Procter & Gamble	0.08456	0.08147	−0.07755	0.34963	0.09489	0.60588
United Technologies	0.02045	0.00281	−0.30968	0.47753	0.18222	0.42342
United Health	0.09783	0.08830	−0.38938	0.64011	0.27515	0.22025
Verizon	0.05485	0.07535	−0.22899	0.25606	0.11801	−0.26195
Wal-Mart Stores	0.08244	0.04671	−0.26663	0.54521	0.16924	0.85901
Walt Disney	−0.01234	−0.00999	−0.38546	0.45742	0.17718	0.12176
DJIA	0.01561	0.03126	−0.27263	0.18910	0.09797	−0.84897

Source: own processing, using data of Stooq.com.

Table A3. Winter period returns—Descriptive statistics.

	Average	Median	Minimum	Maximum	Standard Deviation	Skewness
3M	0.09564	0.11077	−0.11000	0.37462	0.10760	−0.08943
AIG	0.04580	0.04580	−0.27750	0.44797	0.19929	0.16929
Alcoa	0.12058	0.07043	−0.21141	0.58323	0.20908	0.49320
Altria Group	0.07227	0.08561	−0.72243	0.67573	0.24212	−0.68560
American Express	0.12917	0.17464	−0.29195	0.55451	0.20841	−0.06366
Apple	0.19069	0.16511	−0.32930	1.28709	0.34155	1.06544
AT&T	0.04362	0.05471	−0.27722	0.31731	0.12743	−0.28861
Bank of America	0.12684	0.14053	−0.63050	1.19928	0.29594	1.00611
Boeing	0.09624	0.10907	−0.26607	0.51527	0.18444	0.02066
Caterpillar	0.17154	0.19618	−0.27695	0.49856	0.17525	−0.21485
Citigroup	0.07343	0.06851	−0.77654	0.62552	0.26967	−0.43355
Coca-Cola	0.07690	0.05780	−0.23491	0.56077	0.15216	0.69142
DuPont	0.11923	0.10083	−0.40027	0.51214	0.18454	−0.02655
ExxonMobil	0.07340	0.06841	−0.10086	0.32331	0.11061	0.31180
General Electric	0.10747	0.12183	−0.35169	0.35957	0.16295	−0.61715
Goodyear	0.15798	0.16406	−0.31652	1.16991	0.28388	1.28922
Home Depot	0.22614	0.12058	−0.13900	1.27739	0.30259	1.64602
Honeywell	0.13838	0.12971	−0.26587	0.51992	0.16836	0.09513
Chevron	0.08077	0.06402	−0.30149	0.34835	0.13920	−0.09758
IBM	0.07949	0.07548	−0.27295	0.46450	0.16018	0.12500
Intel	0.14732	0.09965	−0.31149	1.33308	0.29778	1.90878
J. P. Morgan	0.14816	0.12413	−0.27173	1.09514	0.24269	1.54701
Johnson & Johnson	0.09278	0.08891	−0.20745	0.48298	0.15734	0.44137
Microsoft	0.16907	0.10092	−0.24637	1.66739	0.35826	2.69267
Navistar	0.21485	0.19149	−0.46789	1.60000	0.45921	1.29692
International Paper	0.09440	0.09244	−0.29395	0.37268	0.16096	−0.69636
McDonald´s	0.12023	0.09401	−0.10744	0.49196	0.14976	0.62815
Merck	0.08022	0.06303	−0.34708	0.50852	0.18567	0.12572
Pfizer	0.08210	0.06972	−0.24559	0.61048	0.17744	0.89238
Procter & Gamble	0.03208	0.04898	−0.43044	0.27004	0.13660	−1.12237
United Technologies	0.13114	0.11373	−0.15185	0.53078	0.14193	0.64883
United Health	0.19072	0.17127	−0.42029	1.23404	0.31932	1.17580
Verizon	0.03721	0.02261	−0.18154	0.44767	0.12712	0.83733
Wal-Mart Stores	0.13014	0.07370	−0.12582	0.58775	0.19795	1.02957
Walt Disney	0.19490	0.18663	−0.15476	0.95379	0.22460	1.12642
DJIA	0.08416	0.08130	−0.12406	0.29812	0.09559	0.17726

Source: own processing, using data of Stooq.com.

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