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The Halloween Effect on Energy Markets: An Empirical Study

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ABSTRACT

Seasonal anomalies play an important role in the global economic system. One of the most frequently empirically observed anomalies is the Halloween effect. Halloween effect describes the anomaly in the financial markets, which is that the returns of different assets in the summer period generally are lower than the returns in the winter period. This study tests the hypothesis of the existence of the Halloween effect on the energy markets over the period from 1985 to 2016. The sample includes series of prices for various energy resources. The econometric estimation showed that for a range of energy markets, returns during the summer period are higher than the returns in winter ones. The difference in returns is statistically significant, which speaks in favor the Halloween effect.

Keywords: Halloween Effect, Financial Market, Energy Market, Bounded Rationality, Investor Sentiment
JEL Classifications: G15; G41; Q41, Q43

1. INTRODUCTION

Financial markets are in constant evolution. Markets are constantly developing new methods of risk analysis. There are new products and technologies that contribute to increasing information asymmetry. But even against the desire of market players to reduce market uncertainty, force of habit as a manifestation of bounded rationality continues to exist. Among the manifestations of bounded rationality in the prevailing habits and traditions are seasonal or calendar anomalies. Calendar anomaly is a cyclic pattern of behavior of players of different markets, characterized by cyclical oscillations in returns in the financial markets. The most common seasonal anomalies are day of the week effect, January effect, the month effect and the Halloween effect. Studies show that not all the calendar anomalies occur in each market. Among the most common cases, the calendar effect is found in equity markets (Lakonishok and Smidt, 1988; Haggard et al., 2015), however some authors found that seasonal anomalies can be present on the markets of different goods (Milonas, 1991; Borowski, 2015).

Since seasonal and calendar anomalies represent irrational form of habits, it is logical to assume that the Halloween effect is in contradiction with the full rationality assumption of the neoclassical school of economic thought. In the case of financial markets, this contradiction is manifested in the inability to describe this seasonal anomaly with the efficient markets hypothesis (Fama, 1965). As follows from the main provisions of the efficient markets hypothesis, the current price of an asset incorporates and reflects all the available information about the asset, respectively, arbitrage opportunities or generating income above the norm on the market simply do not exist when using fundamental or technical analysis. However, empirical observations and studies of many authors showed the existence of data anomalies and confirm the possibility of obtaining abnormal returns, even taking into account transaction costs and adaptive expectations of market players.

2. LITERATURE REVIEW

Halloween effect was first identified on the securities market. The basis of this seasonal anomaly is the assumption, according to which stock returns in the May-October period are significantly lower than in the second half of the year. For example, a study by Bouman and Jacobsen (2002) has shown that the Halloween effect is present in the securities markets of 36 developed and developing countries. Other studies confirmed the results of Bouman and Jacobsen (2002) and have shown that the Halloween effect exists for various stocks and for various segments of the market. For example, a study of Lean (2011) showed the presence of the Halloween effect in the stock markets of several Asian countries (Malaysia, China, India, Japan, Singapore). Jacobsen and Nuttawat (2009) found that 48 out of 49 U.S. sectors of the stock market showed better result in the winter period rather than in the summer period. For 2/3 of the sectors, the difference was statistically significant. The study is based on time series sample from 1926 to 2006. Andrade et al. (2013) came to the conclusion that the Halloween effect not only affects the value of assets, but also on the credit risk premium and volatility. Zhang and Jacobson (2013) examined data on the securities market of Great Britain for a period of more than 300 years. As a result, the authors came to conclusion that calendar and seasonal effects took place, although their scope and importance has changed significantly. The Halloween effect was present constantly regardless of the applied methods.

Commodity markets and commodity prices are under close attention of researchers all over the world. Most of papers pay attention to either food price crisis (Etienne et al., 2014; Hochman et al., 2014) or various factors affecting commodities' prices (Liu, 2014; Ott, 2014; Hamilton and Wu 2015; Burakov, 2017).

Most of attention in the studies of energy market is paid either to the search of causal relationships between energy prices and macroeconomic environment (Ozturk, 2010; Mensi, et al., 2014; Wang et al., 2014), between energy prices and employment (Alkhateeb et al., 2017), the relationship of cost of energy resources and energy efficiency (Ozturk and Acaravci, 2013), or to effects of energy shocks on economic and monetary variables. (Burakov, 2017; Kurnysheva; Burakov, 2017) At the same time studies on seasonal and calendar anomalies in energy markets is almost absent.

It is important to note that energy markets play an important role in the development of national economies of the countries-exporters and the countries-importers of energy resources. The importance of the energy market is determined by the balance between supply and demand. Sudden shocks in energy prices such as oil, gas, coal, can lead to sharp changes in the macroeconomic situation in countries highly dependent on energy rents. For example, the sharp decline in oil prices has a significant impact on economic growth, wages, employment and consumption in the case of exporting countries. In the case of a sharp rise in energy prices, the consequences for the countries-importers of energy resources are increased inflationary pressure in the national economy (as was the case in the United States during the 1970s). Sources of changes in energy prices can be not only due to fundamental changes in supply and demand, but also due to speculative activities of market players. In other words, we assume that the Halloween effect can have a significant impact on dynamics of returns in energy markets.

The purpose of this paper is to investigate the presence of the Halloween effect in energy markets. In the case of confirmation of the hypothesis, the results obtained can be useful both to professional market players and regulators. Also, in case of confirmation of the hypothesis, we get additional confirmation of the weakness of the neoclassical efficient markets hypothesis.

3. MATERIALS AND METHODS

In this paper we investigate the presence of the Halloween effect in different markets for energy resources for the period from 1985 to 2016. For the study we use monthly closing prices for crude oil, coal, hydrocarbons and uranium. Data were provided by the International Monetary Fund (IMF) database. To study the Halloween effect, following Arendas (2017), we divide each calendar year consisting of 12 months into two periods - winter and summer. In case of presence of the Halloween effect, the returns of the winter period should be significantly higher in comparison with the returns of the summer period. The end of summer and the beginning of the winter period will be around Halloween. In this study, a turning point from one period to another is the closing price of the last trading day in October.

Thus, definition of the turning point from the winter period to the summer period is ambivalent. In professional circles it is believed that it is necessary to "sell in May and go away". So, in most papers studying the Halloween effect, the turning point is determined as the last trading day April. In this paper we use two alternative turning points: Closing price of the last trading day in April and the closing price of the last trading day in May. This allows us to study several variations of the Halloween effect.

Such formulation of the problem allows us to propose and test the following hypotheses:

H1: The Halloween effect is present in the energy market.

H2: The observed cases of the Halloween effect are statistically significant.

H3: The returns in the sampled markets follow the similar patterns.

According to the Hypothesis H1, the Halloween effect can be observed in energy markets. If the assumption of this hypothesis is correct, then the returns of the winter period (October-April or October-May) must be higher than the returns of the summer period (May-October or June-October). It is logical to assume that for the selected observation period (32 years) we can certainly find the years in which this assumption is incorrect. However, if the Halloween effect is present in the specific energy market, the number of years of its presence must be more than the number of years of its absence. The same is true for comparisons of average returns of summer and winter periods on 32 years' time span - average returns of summer period should be lower in comparison with the average returns of the winter period.

Hypothesis H2 assumes that the observed cases of the presence of the Halloween effect are statistically significant. Since the average results may be greatly skewed due to the years in which the markets showed abnormal levels of return, the difference between the returns of summer and winter period should be statistically significant to prove the presence of the Halloween effect on the market. Otherwise, this pattern can be considered as a random disturbance on the market caused by an exogenous shock.

Hypothesis H3 introduces the assumption under which the related markets should behave in a similar way. We assume that related markets are influenced by similar factors. And this leads to what should trigger the substitution effect, which in turn should generate similar anomalies on related markets. We expect to see similar patterns of behavior on the sample of markets of oil, natural gas, coal and uranium.

If the Halloween effect is present on a particular market, the average returns of the winter period should be considerably higher in comparison with the average summer returns. To test the hypotheses presented in this paper, we use parametric (Two-sample t-test) and nonparametric (Wilcoxon rank sum test) statistical tests to assess the statistical significance of the difference between the returns of summer and winter period for selected markets.

The Shapiro-Wilk test is used to determine which type of test, parametric or nonparametric, is more suitable to test a particular data. In our case, the Shapiro-Wilk test should show whether the returns come from a normally distributed population. Despite the fact that there is a large number of tests to determine the normality of distribution, Shapiro-Wilk test is considered to be one of the most accurate (Razali and Wah, 2011). A study conducted by Arendas (2017) also shows the possibility of its application to the study of the Halloween effect on selected markets. If returns come from a normally distributed population, it is more appropriate to use the Two-sample t-test. If the returns do not come from a normally distributed population, Wilcoxon rank sum test is more suitable. The use of this test allows to assess the statistical significance of the difference between returns of summer and winter periods.

Two-sample F-test is used to determine the identity of the variances for the returns of summer and winter periods. Depending on the result of the study, we will use Two-sample t-test for equal variances or Two-sample t-test for unequal variances.

The algorithm of the research includes the following steps:

1. We calculate the return for particular markets on a certain time period. Each calendar year is divided into two periods: Winter and summer. Given the differences in the definition of turning points, in the first case the calendar year is divided into periods from the last trading day of October to the last trading day of April of the following year (winter) and from the last trading day of April to the last trading day of October (summer period). In the second case, the summer period lasts from the last trading day of May to the last trading day in October and the winter period - from the last trading day of October through the last trading day of May. Monthly closing prices of energy resources provided from the database of the IMF.

The return is calculated by the following formulas:

$$r_{s_n} = \frac{P_{O_n} - P_{A_n}}{P_{A_n}} \tag{1}$$

$$r_{w_n} = \frac{P_{A_{n+1}} - P_{O_n}}{P_{O_n}} \tag{2}$$

Where: r_{s_n} Is the return for the summer period, r_{w_n} is the return for the winter period, n represents the calendar year, P_{O_n} is the October closing price for year n and P_{A_n} is the April closing price for year n. For the second case, P_{M_n} (May closing price for year n) and $P_{M_{n+1}}$ are used instead of P_{A_n} and $P_{A_{n+1}}$ respectively.

2. We calculate descriptive statistics. The descriptive statistics include the average returns for a specific time period, minimum and maximum returns, as well as the level of the presence of the Halloween effect (the number of years that the Halloween effect has emerged over the 32-year period).
3. To test whether the returns of a given period come from a normally distributed population, we use the Shapiro-Wilk test. Based on the obtained results, we decide whether to use Two-sample t-test or Wilcoxon rank sum test.
4. The Two-sample F-test for variances is used to determine whether the returns of winter and summer periods have equal variances. The result will determine the type of test most appropriate for the study: Two sample t-test for equal variances or Two-sample t-test for unequal variances.
5. The Two-sample t-test is used to determine whether the difference between the returns of summer and winter periods for a particular product are statistically significant.
6. We use Wilcoxon rank sum test, due to its advantages over the Two-sample t-test for data that is not characterized by normal distribution.
7. We evaluate the validity of the hypotheses.

4. RESULTS AND DISCUSSIONS

The results of the study showed that the differences in returns in winter and summer periods in selected markets vary significantly. The same is true for the minimum and maximum returns on the markets. If we turn to the percent of the presence of the Halloween effect, we could see that depending on the turning point and on the particular market, the percentage of its presence also varies significantly.

For the first alternative, where the summer period lasts from May to October and winter period - from November to April, most markets showed returns in winter period significantly higher than in the summer period (Table 1).

The largest difference in returns in the first alternative, are recorded on the coal market in Australia and crude oil in Dubai: Difference in returns is more than 20%. The market for uranium and natural gas (Indonesia) show higher returns during the summer than in winter period.

As we have pointed out before, the level of presence of the Halloween effect varies significantly from one energy market to another. Mostly the Halloween effect is present on the market of crude oil (Dubai), natural gas (Russia) - more than 60% of cases. More than in the half of the years of observation, the Halloween effect is observed on the coal market (Australia), crude oil markets for Brent and West Texas.

Regarding the second alternative, where the turning point is May, results are generally similar to the previous one (Table 2). As in the first alternative, in most cases, the Halloween effect is manifested

Table 1: Halloween effect statistics (alternative 1)

Halloween effect (time span 1)									
Market	Summer returns (May-October)			Winter returns (November-April)			Resulting statistics		
	min, %	max, %	average, %	min, %	max, %	average, %	Halloween effect present, years	Halloween effect absent, years	Halloween effect, %
Fuel (energy) index	−25.3	45.3	−1.5	−37.2	48.2	7.4	22	10	69
Crude Oil (petroleum): Brent, West Texas, Dubai Fateh	−13.4	34.5	−5.25	−25.3	37.4	7.95	18	14	56
Coal (Australian thermal coal)	−18.8	65.4	−2.5	−30.7	68.3	20.7	16	16	50
Natural gas (Russia)	−29.9	70.1	1.7	−41.8	68.6	15.3	20	12	63
Natural gas (Indonesia)	−45.6	84.7	1.25	−53.4	83.2	1.1	11	21	34
Natural gas (USA)	−43.2	77.5	3.65	−51	76	1.4	15	17	47
Crude Oil (petroleum): Brent,	−31.3	63.3	−4.8	−39.1	61.8	13.25	19	13	59
Oil, Dubai	−26.3	65.8	−1.05	−18.5	64.3	24.8	25	7	78
Crude Oil, West texas	−28.6	68.8	−0.7	−36.4	67.3	1.35	18	14	56
Uranium NUEXCO	−19.9	55.2	3.15	−27.7	53.7	−4.9	7	25	22

Source: Author's calculations

Table 2: Halloween effect statistics (alternative 2)

Halloween effect (time span 2)									
Market	Summer returns (May-October)			Winter returns (November-April)			Resulting statistics		
	min, %	max, %	average, %	min, %	max, %	average, %	Halloween effect present, years	Halloween effect absent, years	Halloween effect, %
Fuel (Energy) Index	−31.2	54.2	−9.5	−26.9	58.1	17.5	24	8	75
Crude Oil (petroleum): Brent, West Texas, Dubai Fateh	−19.3	43.4	−8.95	−15	47.3	18.05	19	13	59
Coal (Australian thermal coal)	−39.8	74.3	−3.75	−35.5	78.2	23.25	17	15	53
Natural Gas (Russia)	−37.7	74.6	−2.55	−33.4	78.7	24.55	19	13	59
Natural Gas (Indonesia)	−53.4	89.2	3.1	−49.1	93.3	2.4	11	21	34
Natural Gas (USA)	−51	83.9	4.55	−56.8	88	3.5	15	17	47
Crude Oil (petroleum): Brent,	−37.2	72.2	−3.5	−43	76.1	8.45	17	15	53
Oil, Dubai	−32.2	72.8	−0.7	−38	76.7	7.25	24	8	75
Crude Oil, West Texas	−34.5	65.9	−5.3	−40.3	69.8	16.65	23	9	72
Uranium NUEXCO	−25.8	64.1	1.85	−31.6	68	−2.1	10	22	31

Source: Author's calculations

on the markets of crude oil (Dubai) and West Texas - more than 70%. The same is true for the natural gas market (Russia), as well as oil markets, Brent and coal market (Australia). The largest difference in returns is observed on the markets for coal, natural gas (Russia) and oil (West Texas).

If we compare the average level of the presence of the Halloween effect in the first and second alternative, the first alternative average level of the Halloween effect presence is 53,4%, and in the second alternative - 55,8%.

Table 3 presents the results of Two-sample t-test and Wilcoxon rank sum test. The cases in which the difference between returns in the summer and winter periods is statistically significant (at the significance level 0.05) are in bold. The cases in which a reverse Halloween effect manifested itself (when the returns of the summer periods are higher than returns in winter) are written in italics. Based on the results of Shapiro-Wilk test, we determined which test would be better suited for particular data sets: Parametric Two-sample t-test or nonparametric Wilcoxon rank sum test. The results of a more appropriate test are marked with “ * ”.

Table 3: Statistical tests results

Market	Halloween effect (time span 1)		Halloween effect (time span 2)	
	two-sample t-test	Wilcoxon rank sum test	two-sample t-test	Wilcoxon rank sum test
Fuel (Energy) Index	0.9896*	0.9942	0.9786*	0.9912
Crude Oil (petroleum): Brent, West Texas, Dubai Fateh	0.9214*	0.9557	0.9413*	0.9661
Coal (Australian thermal coal)	0.0325	0.0114*	0.0467	0.0021*
Natural Gas (Russia)	0.0298	0.0193*	0.0412	0.0171*
Natural Gas (Indonesia)	0.0051	0.0032*	0.0041	0.0002*
Natural Gas (USA)	0.0478	0.0496*	0.0319	0.0231*
Crude Oil (petroleum): Brent	0.6723*	0.7245	0.2451*	0.4296
Oil, Dubai	0.0079	0.0042*	0.0041	0.0029*
Crude Oil, West Texas	0.0251	0.0433*	0.0096	0.0031*
Uranium NUEXCO	0.0017	0.0015*	0.0154	0.0087*

Source: Author's calculations

As can be seen from Table 3, both test statistics are in agreement in all cases except the composite indexes (Fuel Index and the Composite Index of Crude oil). Due to the fact that these indices aggregate different markets, the results can be considered statistically insignificant.

As can be seen from Table 3, the statistically insignificant results include the results for the oil market Brent. Three markets show the reverse Halloween effect to be permanently present, where returns in the summer periods exceed the returns in the winter periods. Among these are the markets for natural gas (Indonesia, USA), and the uranium market.

Given the fact that a large part of data sets doesn't follow normal distribution, in most cases, the most appropriate is the Wilcoxon rank sum test. Also the results show that both alternatives for most of markets, are statistically significant and confirm the existence of the Halloween effect on the selected energy markets.

Hypothesis H1, which suggests that the Halloween effect is present in the markets of the energy sector, receives partial support. Halloween effect is present on oil markets and natural gas market (Russia). This result is statistically relevant and valid for both alternatives. The number of years during which the effect of Halloween, present for more than 50%, and for certain markets - 70% of cases. Then we can assume that in some energy markets, the Halloween effect is present in the period from 1985 to 2016.

Hypothesis H2, according to which the observed cases of the Halloween effect are statistically significant in nature, can be partially accepted. Even if not in all cases, the Halloween effect is statistically significant in nature (in some cases, the excess returns of the summer period over the winter period can be the consequence of an exogenous shock that produced the abnormal return). Nevertheless, for most markets, the Halloween effect is present and is statistically significant. We were also able to identify statistically significant cases of the reverse Halloween effect.

Hypothesis H3 (Returns of the related commodities follow similar patterns) can be partially accepted. Although there are some exceptions, the related commodities tend to follow similar patterns in most of the cases. As the data show, the related commodities behave similarly in most of the cases.

It is able to conclude that there is the Halloween effect present on the energy markets. Its strength differs market to market, but in many cases it is strong enough to become a cornerstone of profitable strategies generating abnormal returns even after taking the transaction costs into account.

Even given the fact that there is extensive research on the Halloween effect, consensus on the nature and sources of the Halloween effect doesn't exist. Hong and Yu (2009) attribute the Halloween effect with the summer holidays, when investors go on vacation and trading volumes on the exchanges are significantly reduced. Some authors consider that the Halloween effect's source lies in changes of weather, because the cold and decreasing temperature leads to an increase in aggression, and apathy (Cao and Wei, 2005). For this reason, winter returns tend to be higher, because market players are trading in a more aggressive manner. On the other hand, Jacobsen and Marquering (2008) presented evidence that the weather factor is hardly a Halloween effect's source in the stock market. On the other hand, even if this is true for the stock market, the weather definitely has an impact on the seasonality of trading on the markets of agricultural commodities (Arendas, 2017).

5. CONCLUSION

Analysis of prices for key energy markets for the last 32 years has shown that the Halloween effect is present on energy markets. In five out of seven energy markets with a statistically significant result, we found the presence of the Halloween effect when the average returns of the winter periods of higher than average returns year periods. This result is typical for a number of markets crude oil, natural gas and thermal coal.

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