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The Halloween effect on the agricultural commodities markets

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Abstract: The financial markets are impacted by various seasonal anomalies. One of the best known of them is the Halloween effect. The Halloween effect means that the summer period (May–October) asset returns are lower compared to the winter period (November–April) asset returns. In the paper, price series of 20 major agricultural commodities over the 1980–2015-time period are tested for the presence of the Halloween effect. The data show that 15 out of the 20 commodities recorded a higher average winter period than summer period returns and in 10 cases, the differences are statistically significant. The data also show that out of the 5 commodities with higher summer period returns, only in the case of poultry the differences are statistically significant.

Keywords: abnormal returns, agriculture, commodity, investing, seasonal anomaly

The global financial markets are in a permanent development. Although the technologies and financial instruments evolve and change over time, some aspects of financial markets remain almost unchanged. To these aspects, there belong also various calendar anomalies. The calendar anomalies are the cyclical anomalies in returns that tend to repeating according to various calendar patterns. Although the strength of the anomalies is variable, they can be tracked back to the 18th century. Some of the best known anomalies are the January effect, the day of the week effect, the month of the year effect, the turn of the week/month/year effects and the Halloween effect. Not all of the anomalies are present on all of the markets. Most attention has been paid to the calendar anomalies on share markets (Lakonishok and Smidt 1988; Haggard et al. 2015), but some of the authors investigated also the presence of calendar anomalies on the commodity markets (Milonas 1991; Borowski 2015).

The existence of calendar anomalies is in a direct contradiction to the efficient market hypothesis (Fama 1965). According to the efficient market hypothesis, the asset prices should reflect all of the available information and as a result, it is unable to generate abnormal returns using the technical or fundamental analysis. However, in many cases, the calendar anomalies are able to generate abnormal returns even after the transaction costs are taken into account.

The Halloween effect was first observed on the share markets. It is based on the premise that the share returns tend to be lower during the May–October period than during the second part of the year. A study from Bouman et al. (2002) confirmed the presence of the Halloween effect on the share markets of 36 countries. Various studies confirmed that the Halloween effect is valid for different share markets as well as for different share market segments. For example, the study of Lean (2011) confirmed the presence of the Halloween effect on the share markets in Malaysia, China, India, Japan and Singapore. Jacobsen and Nuttawat (2009) discovered that during the 1926–2006-time period, 48 out of 49 U.S. share market sectors performed better during the winter than during the summer period. In 2/3 of the sectors, the difference was statistically significant. Andrade et al. (2013) concluded that the Halloween effect affects not only the equity values but also the volatility and credit risk premiums. Zhang and Jacobson (2013)

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analysed more than 300 years of the Great Britain share market data and they concluded that various calendar anomalies were present over time, although their extent and significance has been changing significantly. They also found out that the Halloween effect was robust over the full time period, across different estimation methods.

Although the commodities markets and commodities price development are in the centre of attention of many researchers, most of the papers focus on the food price crisis (Etienne et al. 2014; Hochman et al. 2014) and various factors impacting commodities prices (Liu 2014; Hamilton and Wu 2015). Much attention has been paid to the relation between the oil prices and agricultural commodities prices (Mensi et al. 2014; Wang et al. 2014). On the other hand, only a little attention has been paid to the Halloween effect and other seasonal patterns on commodities markets, let alone on agricultural commodities markets.

Agricultural commodities markets are specific, due to the high importance of the supply-demand balance. They are also known for very strong seasonal patterns that are related to the production cycles. Given that these markets are also influenced by speculations and some of the other economic factors affecting the share markets, it is able to expect the presence of some of the share market seasonal anomalies to show on the agricultural commodities markets as well. For example, the soybean market is well known for its strong seasonal pattern when the soybean prices tend to peak during the May–July period and they tend to bottom in October (Arendas 2015) which indicates a high probability of presence of the Halloween effect. The aim of this paper is to investigate the presence of the Halloween effect on the agricultural commodities markets. If the presence of the Halloween effect is confirmed, it may be helpful to the investors as well as to hedging activities of the agribusiness subjects.

MATERIAL AND METHODS

This paper investigates the presence of the Halloween effect on 20 agricultural commodities markets over the last 35 years. Barley, beef, coarse wool, cocoa, coffee Arabica, coffee Robusta, corn, cotton, fine wool, hides, palm oil, pork, poultry, rice, rubber, soybean, soybean meal, soybean oil, sugar and wheat monthly closing prices for the 1980–2015 time period are investigated. The data were provided by the International Monetary Fund (IMF) database.

To investigate the Halloween effect, every year (12 consecutive months) was divided into two parts (the summer period and winter period), reflecting the traditional Halloween effect definition. If the Halloween effect is present, the winter period returns are significantly higher compared to the summer period returns. The end of the summer period and the start of the winter period should occur around the Halloween. In this paper, this turning point is defined as the closing price of the last trading day in October. On the other hand, most of the investors and analysts define the second turning point (the end of the winter period and the start of the summer period) more vaguely. The common wisdom defines it as “sell in May and go away”. Although most of the researchers use the last April trading day as the turning point, this paper uses two alternatives of this turning point: the closing price of the last trading day of April and the closing price of the last trading day of May. As a result, two variations of the Halloween effect are investigated.

The following hypotheses are tested:

– H1: There is a Halloween effect present on the agricultural commodities markets.
– H2: The observed cases of the Halloween effect are statistically significant.
– H3: Returns of the related commodities follow similar patterns.

Hypothesis H1 assumes that the Halloween effect can be observed on the agricultural commodities markets. If this assumption is correct, the returns of the summer period (May–October or June–October) should be lower compared to the returns of the winter period (October–April or October–May). It is highly likely that there were years when this assumption was incorrect, over the 35-year period. However, if there is a Halloween effect present on a particular market, the number of years when this assumption holds should outnumber the number of years when it does not hold and also the average summer period returns for the whole 35-year time period should be lower compared to the average winter period returns.

Hypothesis H2 assumes that the observed cases of the Halloween effect are statistically significant. As the average results may be significantly skewed by a couple of years with extreme returns, the differences between the summer period and winter period returns must be statistically significant in order to confirm that the Halloween effect is really present and that the pattern is not only a question of chance.

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Hypothesis H3 assumes that the related markets should behave similarly. It is possible to assume that the related markets are impacted by similar factors and the substitution effect should result in the existence of similar anomalies on the markets of the related commodities. Out of the 20 agricultural commodities, similar patterns are expected in the following subgroups:

- Cereals – barley, corn, rice, wheat
- Meats – beef, pork, poultry
- Oils – palm oil, soybean oil
- Soybean and soybean products – soybean, soybean oil, soybean meal
- Coffees – coffee Arabica, coffee Robusta
- Wools – coarse wool, fine wool

If the Halloween effect is present on a particular market, the average summer period returns should be significantly lower compared to the average winter period returns. Parametric (Two-sample t-test) and non-parametric (Wilcoxon rank sum test) statistical tests are used to evaluate whether the differences between returns are statistically significant.

The Shapiro-Wilk test is used to determine whether the parametric or non-parametric test is more meaningful for the particular dataset. The Shapiro-Wilk test shows whether the returns come from a normally distributed population. There are various statistical tests to investigate the normality of distribution, however, the Shapiro-Wilk test is the most powerful one (Razali and Wah 2011). If the returns come from a normally distributed population, the Two-sample t-test is more suitable. If the returns do not come from a normally distributed population, the non-parametric Wilcoxon rank sum test would be more suitable to evaluate the statistical significance of differences between the summer and winter period returns.

The Two-sample F-test is used to determine whether the summer period and winter period returns have the same variances. Based on the results, it is possible to determine whether the two-sample t-test for equal variances or two-sample t-test for unequal variances should be used for the particular datasets.

The statistical tests are performed using the MS Excel and the statistical software Gretl.

The whole process can be summed up into the following steps:

(1) Returns of the particular commodities during the particular time periods are calculated. The calendar year is divided into two parts. In the first case, the year is divided into time periods from the last trading day of April to the last trading day of October (summer period) and from the last trading day of October to the last April trading day of the following year (winter period). In the second case, the first period starts on the last trading day of May and it ends on the last trading day of October (summer period) and the second period lasts from the last trading day of October to the last May trading day of the following year (winter period). Monthly closing commodity prices from the International Monetary Fund databases are used.

The returns are calculated using the following formulas:

$$r_{s_x} = \frac{P_{O_x} - P_{A_x}}{P_{A_x}} \quad (1)$$

$$r_{w_x} = \frac{P_{A_{x+1}} - P_{O_x}}{P_{O_x}} \quad (2)$$

where: r_s is the return for the summer period, r_w is the return for the winter period, x represents the calendar year, P_{OX} is the October closing price in year x and P_{AX} is the April closing price in year x. For the second alternative, P_{MX} (May closing price in year x) and P_{MX+1} are used instead of P_{AX} and P_{AX+1}.

(2) Basic statistics are calculated. The statistics include the average returns for the particular time periods, the maximal and minimal returns and the success rate of the Halloween effect (how many times the Halloween effect occurred over the analysed 35-year time period).

(3) The Shapiro-Wilk test is performed in order to determine whether the returns for the particular time periods come from a normally distributed population. Based on the results of the Shapiro-Wilk test, it is decided whether the Two-sample t-test or the Wilcoxon rank sum test will be more appropriate.

(4) The Two Sample F-test for variance is performed in order to determine whether the summer and winter period returns have the same variances. Based on the results, it is determined whether the Two-sample t-test for equal variances or the Two-sample t-test for unequal variances should be used for the particular datasets.

(5) The Two-sample t-test is performed in order to determine whether the differences between the returns of the summer and winter periods for the particular commodities are statistically significant.

(6) The Wilcoxon rank sum test is performed. The Wilcoxon rank sum test is a non-parametric alter-

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native to the two-sample t-test. It is more accurate than the two-sample t-test for the datasets that do not come from a normally distributed population.

(7) The validity of the hypotheses is evaluated.

RESULTS AND DISCUSSION

The results show that the differences between the average summer period and winter period returns vary significantly commodity to commodity. Also the minimum and maximum returns as well as the percentage of years of the Halloween effect vary significantly. There are notable differences between the results of the two alternatives of the Halloween effect as well.

Taking into account the first alternative (the summer period lasts from the beginning of May to the end of October and the winter period lasts from the beginning of November to the end of April), 15 out of the 20 surveyed agricultural commodities recorded higher returns during the winter period than during the summer period (Table 1). The biggest differences were recorded by the fine wool and palm oil where the average returns differed by more than 12 percentage points. Only beef, hides, poultry, sugar and wheat had higher average summer period than the average winter period returns. Out of these five commodities, the highest difference can be seen in the case of sugar, where the average summer period returns are higher by more than 9 percentage points.

As stated above, the success rate (% of years of the Halloween effect) differs significantly commodity to commodity. The Halloween effect can be most often observed on soybean, soybean oil, palm oil, cotton and corn markets, where the winter period

Table 1. Halloween effect – alternative 1 – statistics

	Halloween effect – alternative 1								
	summer period returns (May–October)			winter period returns (November–April)			statistics		
	minimum (%)	maximum (%)	average (%)	minimum (%)	maximum (%)	average (%)	Halloween effect years	non-Halloween effect years	success rate (%)
Barley	−39.30	33.76	−0.99	−22.90	33.08	5.89	20	15	57
Beef	−19.14	39.59	1.46	−19.67	36.72	1.42	16	19	46
Coarse wool	−38.07	43.94	−2.82	−16.01	58.97	6.93	24	11	69
Cocoa	−23.31	40.39	0.41	−28.51	44.55	1.85	18	17	51
Coffee Arabica	−52.64	122.66	−2.56	−39.57	76.19	8.44	22	13	63
Coffee Robusta	−41.32	134.15	−0.78	−31.91	67.81	4.03	15	20	43
Corn	−35.66	49.50	−3.17	−12.86	50.33	7.95	26	9	74
Cotton	−48.94	43.68	−4.67	−15.98	71.17	7.80	26	9	74
Fine wool	−41.89	37.56	−3.97	−33.91	62.99	9.34	21	14	60
Hides	−30.04	84.86	4.21	−57.46	34.58	1.83	18	17	51
Palm oil	−55.11	60.14	−4.16	−32.02	52.82	9.88	27	8	77
Pork	−44.28	110.10	1.05	−40.15	52.26	4.78	18	17	51
Poultry	−7.44	24.07	4.62	−16.54	16.05	−0.31	13	22	37
Rice	−38.53	35.91	−0.55	−31.32	202.78	4.75	19	16	54
Rubber	−32.01	45.14	−2.02	−19.23	67.88	6.33	22	13	63
Soybean	−46.79	44.37	−3.25	−11.57	35.14	7.69	28	7	80
Soybean meal	−50.12	56.09	0.87	−27.98	39.88	4.25	19	16	54
Soybean oil	−38.01	58.18	−3.17	−22.56	46.85	7.40	26	9	74
Sugar	−38.39	90.82	7.93	−56.03	66.27	−1.43	15	20	43
Wheat	−34.47	69.00	3.52	−27.16	24.38	0.61	20	15	57

Source: own calculations

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returns are higher than the summer period returns in more than 70% of the cases. On the other hand, beef, coffee Robusta, poultry and sugar experienced the Halloween effect in less than 50% of the cases.

Regarding the second alternative (the summer period lasts from the beginning of June to the end of October and the winter period lasts from the beginning of November to the end of May), 15 out of the 20 agricultural commodities recorded higher returns during the winter period (Table 2). The biggest differences were recorded by the fine wool, palm oil and pork (more than 15 percentage points). Out of these five commodities with higher summer period than winter period returns, the biggest difference can be seen at sugar (over 9 percentage points).

The highest success rate was achieved by soybean, pork, soybean oil, palm oil and corn. All of the five commodities crossed the 70% mark, soybean climbed even to the 83% level. On the other hand, only cocoa and sugar experienced the Halloween effect in less than 50% of cases.

Comparing the average success rates of the two surveyed Halloween effect alternatives, the Halloween effect occurred in 59% cases of the first alternative and in 63% cases of the second alternative. As shown by Figure 1, also the difference between the average winter period and summer period returns is bigger in the second alternative in most of the cases.

Table 3 shows results of the Two-sample *t*-test and Wilcoxon rank sum test. The cases, where the differences between the summer period and winter period results are statistically significant at the 0.05 significance level are highlighted. The cases, where the summer period returns are higher compared to the winter period returns, e.g. there is a "reverse Halloween effect" are written in italics. Based on

Table 2. Halloween effect – alternative 2 – statistics

	Halloween effect – alternative 2								
	summer period returns (May–October)			winter period returns (November–April)			statistics		
	minimum (%)	maximum (%)	average (%)	minimum (%)	maximum (%)	average (%)	Halloween effect years	non-Halloween effect years	success rate (%)
Barley	–39.57	38.67	–2.84	–10.15	32.32	7.93	22	13	63
Beef	–12.11	37.20	1.96	–25.37	30.91	0.73	19	16	54
Coarse Wool	–34.70	27.81	–3.42	–18.31	57.37	7.59	22	13	63
Cocoa	–23.20	37.19	1.49	–35.71	47.92	1.77	15	20	43
Coffee Arabica	–51.13	62.88	–4.56	–33.84	119.28	10.14	21	14	60
Coffee Robusta	–41.49	77.08	–2.75	–28.87	84.28	5.60	19	16	54
Corn	–38.06	43.92	–3.71	–11.87	48.37	8.36	25	10	71
Cotton	–33.17	40.50	–4.60	–19.96	56.81	7.48	23	12	66
Fine Wool	–38.34	24.10	–5.72	–25.87	65.29	11.13	24	11	69
Hides	–30.71	75.88	3.43	–55.29	34.73	2.80	21	14	60
Palm Oil	–55.25	55.32	–4.79	–35.05	75.37	11.02	26	9	74
Pork	–43.90	98.46	–6.36	–24.12	67.38	13.72	28	7	80
Poultry	–7.82	25.41	3.19	–13.81	17.60	1.12	18	17	51
Rice	–38.18	38.92	0.59	–34.29	201.02	3.74	18	17	51
Rubber	–36.68	39.69	–2.21	–18.22	56.46	6.44	24	11	69
Soybean	–44.40	39.45	–5.00	–14.60	36.46	9.52	29	6	83
Soybean Meal	–48.31	50.93	–1.33	–30.05	40.30	6.45	24	11	69
Soybean Oil	–39.21	56.21	–4.24	–26.33	51.21	8.69	26	9	74
Sugar	–35.77	78.29	7.33	–62.81	55.82	–2.09	14	21	40
Wheat	–31.97	71.24	3.67	–25.41	31.17	0.24	20	15	57

Source: own calculations

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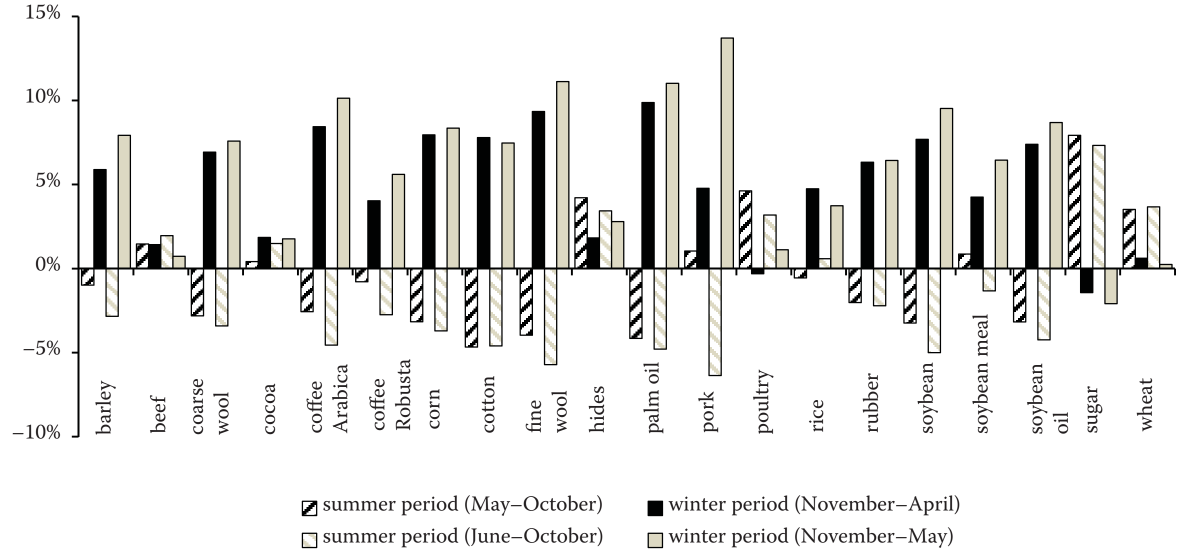

Figure 1. Average returns for the particular time periods

Source: own calculations

the results of the Shapiro-Wilk test, it was decided whether the results of the parametric Two sample *t*-test or the non-parametric Wilcoxon rank sum test are more suitable for the particular dataset. The results of the more suitable test are in bold in Table 3. However, it is possible to see that the results of the two statistical tests are in agreement in all of the cases except of the case of the Halloween effect – alternative 1 and the coffee Arabica, where the Two-sample *t*-test showed that the differences between the summer and winter period returns of the coffee Arabica were not statistically significant while the

Table 3. Statistical tests results (two-tailed *p*-values)

	Halloween effect – alternative 1		Halloween effect – alternative 2	
	two sample *t*-test	Wilcoxon rank sum test	two sample *t*-test	Wilcoxon rank sum test
Barley	**0.09917**	0.23317	**0.01079**	0.02848
Beef	*0.98702*	***0.94849***	*0.61972*	***0.80062***
Coarse wool	0.01426	**0.01215**	0.00442	**0.00588**
Cocoa	**0.70633**	0.75559	**0.94560**	0.80971
Coffee Arabica	0.09321	**0.02166**	0.02238	**0.03816**
Coffee Robusta	0.41696	**0.14688**	0.13111	**0.16042**
Corn	0.01405	**0.00423**	0.00699	**0.00365**
Cotton	0.00906	**0.01215**	0.00848	**0.00896**
Fine wool	0.00976	**0.01683**	0.00089	**0.00197**
Hides	*0.88339*	***0.56095***	*0.53572*	***0.25701***
Palm oil	**0.00830**	0.00654	**0.00498**	0.00753
Pork	0.53572	**0.25701**	0.00164	**0.00016**
Poultry	*0.00540*	***0.00528***	*0.22352*	***0.34437***
Rice	0.42810	**0.80971**	0.64291	**0.68530**
Rubber	0.08131	**0.08964**	0.05524	**0.06602**
Soybean	**0.00753**	0.00314	**0.00050**	0.00032
Soybean meal	**0.43473**	0.44167	**0.07794**	0.06956
Soybean oil	**0.01074**	0.00302	**0.00237**	0.00087
Sugar	***0.18786***	*0.32093*	***0.16740***	*0.18247*
Wheat	***0.51733***	*0.64267*	*0.44833*	***0.95785***

Source: own calculations

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Wilcoxon rank sum test showed that the differences were statistically significant. However, given that the data sets are not normally distributed, the Wilcoxon rank sum test is more appropriate in this case and it is possible to conclude that the Halloween effect is statistically significant.

The results show that both alternatives of the Halloween effect are statistically significant in the case of coarse wool, coffee Arabica, corn, cotton, fine wool, palm oil, soybean and soybean oil. In the case of barley and pork, only the second alternative is statistically significant. There is only one case of the statistically significant "reverse Halloween effect". The May–October poultry returns are statistically higher compared to the November–April poultry returns.

Hypothesis H1 (There is a Halloween effect present on the agricultural commodities markets.) can be fully accepted. 15 out of the 20 agricultural commodities had higher average winter period than the summer period returns. This result is valid for both alternatives of the Halloween effect that were surveyed. Moreover, in the case of 16 commodities (alternative 1) and 18 commodities (alternative 2), the number of the Halloween effect years was higher than 50% during the 35-year time period. It is able to conclude that the Halloween effect is present on the agricultural commodities markets over the 1980–2015 time period.

Hypothesis H2 (The observed cases of the Halloween effect are statistically significant.) can be partially accepted. Although not all of the cases of Halloween effect were statistically significant, which means that the higher winter period returns could be only result of some extreme events, there are 8 (alternative 1) and 10 (alternative 2) cases of the statistically significant Halloween effect. Moreover, one case of the statistically significant "reverse Halloween effect" has been identified as well.

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. The "oils" subgroup (palm oil, soybean oil) and "wools" subgroup (coarse wool, fine wool) behaved according to the Halloween effect pattern, moreover, in the case of all of the four commodities, the Halloween effect was statistically significant. Also in the "soybean and soybean products" subgroup (soybean, soybean oil, soybean meal) and "coffees" subgroup (Arabica, Robusta) all of the commodities followed the Halloween effect pattern. Regarding the "cereals" subgroup, barley, corn and rice had higher average winter period returns although wheat had higher average summer period returns. In the "meats" subgroup, beef and poultry had higher average summer period returns, although pork had higher average winter period returns. As the data show, the related commodities behave similarly in most of the cases. There are only a couple of exceptions that should probably be attributed to some specifics in the production cycles.

It is able to conclude that there is the Halloween effect present on the agricultural commodities markets. Its strength differs commodity to commodity, but in many cases (e.g. pork, soybean, cotton, etc.), it is strong enough to become a cornerstone of profitable strategies generating abnormal returns even after taking the transaction costs into account.

Although various authors paid attention to the Halloween effect, still a consensus about the origins of this phenomenon is missing. Hong and Yu (2009) link the Halloween effect to the summer vacation period, as the investors take a break and trading volumes decline rapidly. Some of the authors claim that the Halloween effect is weather-driven, as colder temperatures can lead to aggression, while high temperatures can lead to aggression as well as to apathy (Cao and Wei 2005). This is why the winter returns tend to be higher, as the market participants trade more aggressively. On the other hand, Jacobsen and Marquering (2008) think that connecting the Halloween effect with weather is premature. But even though it can be premature in the case of the share markets, the weather definitely impacts the Halloween effect pattern on the agricultural commodities markets. Also Ott (2014) concluded that the intra-year agricultural commodity price volatility is significantly affected by the stock-to-use ratio. Weather has a significant impact on the production cycles of the agricultural commodities and on the stock levels and although it probably is not the factor fully responsible for the Halloween effect, it must be taken into account as an important factor when talking about the Halloween effect on the agricultural commodities markets.

CONCLUSION

The analysis of prices of 20 major agricultural commodities over the last 35 years shows that the Halloween effect is present also on the agricultural commodities markets. 15 out of the 20 surveyed agricultural commodities had higher average winter

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period than the average summer period returns, and in one half of the cases the differences between the summer period and winter period returns were statistically significant. Although the researchers have not identified the origins of the Halloween effect reliably yet, it is possible to generate meaningful returns in the long run. This paper shows that in the case of many agricultural commodities, the difference between the summer period and winter period returns is so large that this seasonal anomaly is able to generate abnormal returns. This seasonal anomaly can be exploited by the retail as well as institutional investors and it can be useful also to the agribusiness subjects.

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