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Are soft commodities markets affected by the Halloween effect?

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Abstract: Within the last three decades commodity markets, including soft commodities markets, have become more and more like financial markets. As a result, prices of commodities may exhibit similar patterns or anomalies as those observed in the behaviour of different financial assets. Their existence may cast doubts on the competitiveness and efficiency of commodity markets. It motivates us to conduct the research presented in this paper, aimed at examining the Halloween effect in the markets of basic soft commodities (cocoa, coffee, cotton, frozen concentrated orange juice, rubber and sugar) from 1999 to 2020. This long-time span ensures the credibility of results. Apart from performing the two-sample *t*-test and the rank-sum Wilcoxon test, we additionally investigate the autoregressive conditional heteroskedasticity (ARCH) effect. Its presence in our data allows us to estimate generalised autoregressive conditional heteroskedasticity [GARCH (1, 1)] models with dummies representing the Halloween effect. We also investigate the impact of the January effect on the Halloween effect. Results reveal the significant Halloween effect for cotton (driven by the January effect) and the significant reverse Halloween effect for sugar. It brings implications useful to the main actors in the market. They may apply trading strategies generating satisfactory profits or providing hedging against unfavourable changes in soft commodities prices.

Keywords: calendar anomalies; generalised autoregressive conditional heteroskedasticity model; softs; *t*-test; Wilcoxon rank-sum test

Calendar effects are anomalies in the performance of asset prices and phenomena of abnormal returns whose presence state in contradiction to the efficient market hypothesis (EMH). According to EMH all information should be incorporated in the quotations thus calendar effects should not exist. The concept of market informational efficiency was introduced by Fama (1965) and originally related to financial markets. Today, a plethora of papers examining the informational efficiency of those markets exists (Caporale and Zakirova 2017; Zahng et al. 2017; Rossi 2018; Boya 2019). The analysis of efficiency of commodity markets is also fruitful, focusing on the markets of oil, gold or some agricultural products, such as wheat, corn, and soybean. Relatively little work has been done on the efficiency of soft commodities markets (Gordon 1985; Sabuhoro and Larue 1997; Lokare 2007; Borowski 2015a, b; Krawiec and Górska 2019).

The best-recognised calendar anomalies are: the day of the week effect, the month of the year effect, the turn of the month effect and the Halloween effect. The Halloween effect was first described by Bouman and Jacobsen (2002). This is an equity return anomaly in which the months of November through April provide higher returns than the remaining months of the year. Therefore, it is believed that the best solution for an investor is to withdraw money from the stock exchange in May and then return already in autumn when there is a significant recovery and growth on the stock market. Some argue that the origin of this concept can be traced back to the United Kingdom in the 1930s. Then the privileged class left London after the winter

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season and went to their country residences on vacation ignoring investment portfolios. In autumn they returned to the city and restarted their investments. According to Haggard and Witte (2010), the Halloween effect is perhaps of greater interest to investors than most other anomalies, because the trading rule is simple to implement with low transaction costs, making exploitation of this anomaly potentially profitable.

Since the fundamental work by Bouman and Jacobsen (2002), who analysed stock returns across 37 countries from January 1970 through August 1998 finding a Halloween effect in 36 of these markets, the effect has received much attention. Thus, there exists a large body of literature examining this phenomenon in stock markets. For example, Zhang and Jacobsen (2013) analysed the historical 300-year data of the Great Britain stock market using different methods and they revealed the robust Halloween effect over the full-time period. Guo et al. (2014) confirmed a significant Halloween effect on the Chinese stock market over the 1997–2013 period. Carrazedo et al. (2016) documented the existence of the Halloween effect on the European stock market from October 1992 to October 2010. Arendas et al. (2018) analysed 35 major US stock companies that were covered by the Dow Jones Industrial Average during the 1980–2017 period and showed that 28 of them followed the Halloween effect. Rosini and Shenai (2020) examined calendar effects on the London Stock Exchange over a 10-year period: 2007–2016 using two major indices (Financial Times Stock Exchange 100 and Financial Times Stock Exchange 250) and did not find any evidence of the Halloween effect. Finally, Kenourgios and Samios (2021) investigated the existence of the Halloween effect in stock markets using 118 European equity mutual funds data for the period 2008–2017. They provided evidence of a robust Halloween effect in the European equity mutual funds market even when controlled for other seasonal anomalies.

The Halloween effect in commodities markets was also investigated, but not to the same extent (Borowski 2015c; Arendas 2017; Burakov and Freidin 2018; Burakov et al. 2018). Borowski (2015c) tested the Halloween effect for 39 commodities: base metals, energy products, agricultural items (including soft commodities) and precious metals in several periods of different lengths ranging from 9 years for barley (December 2006–May 2015) to 65 years for copper (January 1950–May 2015). He performed parametric tests for equality of two means and for equality of two variances and confirmed the presence of the Halloween effect for gasoline, gold, heating oil, lean hogs, nickel, rubber, tin, and wheat.

Arendas (2017) investigated 20 agricultural commodities markets (barley, beef, coarse, cocoa, arabica coffee, robusta coffea, corn, cotton, fine wool, hides, palm oil, pork, poultry, rice, rubber soybean, soybean meal, soybean oil, sugar, wheat and wool) using monthly closing prices for the 1980–2015 period. He performed the two-sample *F*-test for variance, the two-sample *t*-test for two means, and the Wilcoxon rank-sum test. The latter is a non-parametric alternative for the two-sample *t*-test. He discovered the significant Halloween effect for barley, coarse wool, arabica coffee, corn, cotton, fine wool, palm oil, pork, poultry, soybean, soybean oil.

Burakov and Freidin (2018) tested the Halloween effect on agricultural commodities markets over the period from 1980 to 2016. They used monthly closing prices of bananas, barley, beef, coarse wool, cocoa, arabica coffee, robusta coffee, corn, cotton, fine wool, fish meal, hides, lamb, olive oil, oranges, palm oil, pork, poultry, rice, rubber, soybean, soybean meal, soybean oil, sugar, sunflower oil, tea and wheat. They applied the same methodology as Arendas (2017) and detected the Halloween effect for bananas, barley, coarse wool, arabica coffee, corn, cotton, fine wool, lamb, olive oil, oranges, palm oil, pork, poultry, soybean, soybean oil, sunflower oil and tea.

Next, Burakov et al. (2018) made identical research for energy markets, that was based on monthly closing prices of crude oil, coal, hydrocarbons and uranium in the period from 1985 to 2016. They reported a significant Halloween effect in oil markets and the natural gas market (Russia). Three markets whose summer period returns exceeded winter period returns exhibited the reverse Halloween effect. These were the markets of natural gas (Indonesia and the USA) and the uranium market.

Although the studies related to agricultural products covered some of the softs (coffee, cocoa, sugar, cotton and rubber), to our best knowledge there are no more recent papers investigating the Halloween effect in markets of soft commodities. In our opinion, it is worth revising the former results and extending the research. Soft commodities (agricultural products grown in tropical regions) are important to the world economy as a significant element of trade in commodity markets. Even though coffee, cocoa, sugar and orange juice are consumption products, they are also used in several industries: coffee and cocoa in cosmetics and pharmaceutical industries, whereas sugar is processed into biofuel. Cotton is used in the textile industry. Rubber also finds many applications and is one of the most important industrial agro-raw materials (Eller and Sagerer 2008).

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The largest coffee producer is Brazil with an amount of 4.1 million t (69 million of 60-kg bags) in 2020, followed by Vietnam, Indonesia and Colombia. Brazil is also the largest sugar producer. The country produced 29.93 million metric t of sugar during the crop year 2019/2020. The second largest producer is India followed by European Union and China. Cocoa is mainly cropped at the Ivory Coast whose production reached 2.15 million metric t in the crop year 2018/2019. Cotton is grown in more than ninety countries worldwide, of which China, India and the US are the most important producers with 61% of total world production in the crop year 2020/2021. In that period, cotton production in China amounted to around 6.42 million metric t. The most important producers of orange juice are: Brazil (1.1 million metric t in 2019/2020) accounting for 55% of total volume and then the US and Mexico. Natural rubber is mainly produced in South and Southwest Asia. In 2020 Thailand produced 4.4 million metric t, becoming the leading producer worldwide (Statista 2021).

With no doubt, soft commodities are significant items in the current accounts and budget revenues of many countries. And within the last three decades these markets, like other commodities markets, have become more and more like financial markets. This process is called 'financialisation of commodity markets'. As a result prices of commodities may exhibit similar patterns or anomalies as those observed in the behaviour of different financial assets. The presence of synchronised changes in the behaviour of different commodity prices may cast doubts on the competitiveness and efficiency of commodity markets. It motivates us to conduct the research presented in this paper. It is aimed at examining the Halloween effect in the markets of basic soft commodities (cocoa, coffee, cotton, frozen concentrated orange juice, rubber and sugar) from 1999 to 2020. Unlike Borowski (2015c), Arendas (2017) or Burakov and Freidin (2018), we not only perform statistical tests but also estimate generalised autoregressive conditional heteroskedasticity (GARCH) models with dummy variables.

MATERIAL AND METHODS

The data set covers monthly closing prices of six soft commodities: cocoa (in GBP/t), coffee (in USD/lb), cotton (in USD/lb), frozen concentrated orange juice (in USD/lb), rubber [in Japanese yen (JPY)/kg] and sugar (USD/lb) from October 1999 to October 2020 that are the basis for calculating continuously compounded returns: $r_t = \ln(p_t/p_{t-1})$. The original data on daily closing prices used to calculate monthly prices (5 501 observations for each commodity) was provided by Bloomberg (2020). The monthly prices were computed as arithmetic means.

The whole research consists of several subsequent steps.

First, we calculate basic monthly statistics for two separate periods: winter (November to April) and summer (May to October). The statistics include the average returns, maximal and minimal returns, standard deviations, skewness and kurtosis.

We run the Jarque-Bera (JB) test in order to verify whether the soft commodities returns follow the normal distribution. The null hypothesis (H_0) is tested against the alternative hypothesis (H_1):

H_0: The returns follow a normal distribution.

H_1: The returns do not follow a normal distribution.

The test statistic JB is (Füss et al. 2008):

$$JB = \frac{n}{6}\left[A^2 + \frac{1}{4}\left(K-3\right)^2\right] \tag{1}$$

where: n – number of observations; A – skewness (third central moment); K – kurtosis (fourth central moment).

The statistic follows an asymptotic chi-squared distribution with two degrees of freedom.

The simplest way to check whether the winter and summer returns (r) differ significantly is to run the two-sample t-test. We use this test in order to verify the null hypothesis (H_0) against the alternative hypothesis (H_1):

H_0: $E(r_1) = E(r_2)$

H_1: $E(r_1) \neq E(r_2)$

The test statistic is given by (Wackerly et al. 2008):

$$t = \frac{\overline{r}_1 - \overline{r}_2}{SD\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \tag{2}$$

where: $\overline{r}_1$ – arithmetic mean calculated for sample 1 (summer returns); $\overline{r}_2$ – arithmetic mean calculated for sample 2 (winter returns); n_1, n_2 – numbers of observations, respectively in the first and the second samples; SD – standard deviation given by:

$$SD = \sqrt{\frac{\left(n_1-1\right)S_1^2 + \left(n_2-1\right)S_2^2}{n_1+n_2-2}} \tag{3}$$

where: S_1^2 – variance calculated for the first sample (summer returns); S_2^2 – variance calculated for the second sample (winter returns).

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For large samples t-statistic follows the normal distribution.

We also use the non-parametric Wilcoxon rank-sum test to check whether the winter and summer returns differ significantly. The decision to use this non-parametric test is justified by the fact that often soft commodities returns are not normally distributed. The Wilcoxon rank-sum test is valid for data from any distribution, whether normal or not. The test is based solely on the order in which the observations from the two dependent samples were selected from populations having the same distribution. This test is much less sensitive to outliers than the two-sample t-test and responds to other differences between the distributions e.g. differences in shape. When the assumptions of the two-sample t-test are met, the Wilcoxon test is slightly less likely to detect a location shift than is the two-sample t-test (Wild and Seber 2000).

For samples of observations from each of two populations 1 and 2 containing n_1 and n_2 observations respectively we test the hypothesis that the distribution of X-measurements in population 1 is the same as that in population 2. The Wilcoxon test is based upon ranking the $n_1 + n_2$ observations of the combined sample.

The test statistic of the Wilcoxon rank-sum test is the sum of the ranks for observations from one of the samples. For larger samples ($n > 10$), we can use the boundary normal distribution $N(\mu_1, \sigma_1)$, with:

$$\mu_1 = \frac{n_1\left(n_1 + n_2 + 1\right)}{2} \tag{4}$$

where: μ_1 – mean; n_1, n_2 – numbers of observations in samples 1 and 2, respectively.

$$\text{and } \sigma_1 = \sqrt{\frac{n_1 n_2\left(n_1 + n_2 + 1\right)}{12}} \tag{5}$$

where: σ_1 – standard deviation.

The test statistic z is:

$$z = \frac{w_1 - \mu_1}{\sigma_1} \sim N\left(0, 1\right) \tag{6}$$

where: w_1 – sum of ranks for observations from one of the samples.

In the next step, we perform a test of autoregressive conditional heteroskedasticity (ARCH) effects, which is the ARCH(q) test proposed by Engle (1982). Engle and others working on ARCH models recognised that past financial data influences future data (that is the definition of autoregressive). The conditional heteroskedasticity portion of ARCH simply refers to the observable fact that volatility in financial markets is nonconstant – all financial data, whether stock market values, commodity prices, exchange rates, or inflation rates, go through periods of high and low volatility. For further details see Ramanathan (2002), Gujarati (2003) or Maddala (2005).

In the Engle test the following model is considered:

$$\varepsilon_t^2 = \lambda_0 + \sum_{i=1}^{q} \lambda_i \varepsilon_{t-1}^2 + \xi_t \tag{7}$$

where: ε_t^2– dependent variable [squared residual from autoregression AR(q) model]; λ_0, λ_i – model parameters; ξ – error term.

The null hypothesis (H_0) is tested against the alternative hypothesis (H_1):

H_0: $\lambda_1 = \lambda_2 = \ldots = \lambda_q = 0$

H_1: $\underset{i}{\exists} \lambda_i \neq 0$

The Lagrangian multiplier (LM) test statistic is:

$$LM = T \times R^2 \tag{8}$$

where: T – number of observations; R^2 – coefficient of determination for Equation (7).

The statistic follows an asymptotic chi-squared distribution with q degrees of freedom.

Finally, to test the existence of the Halloween effect we estimate the following GARCH (1, 1) model with dummy variable:

$$r_t = \mu + \alpha_1 S_t + \varepsilon_t \ \text{ with } \varepsilon_t \middle| \Omega_{t-1}: N\left(0, \sigma_t^2\right) \tag{9}$$

where: r_t – continuously compounded monthly returns; μ, α_1 – model parameters; S_t – seasonal dummy variable that takes the value of 1 if month t falls in the November–April period and 0 otherwise; ε_t – error term; Ω_{t-1} – domain of ε_t; σ_t^2 – conditional variance at time t.

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{10}$$

where: ω, α, β – model parameters; σ_{t-1}^2 – conditional variance at time $t - 1$.

$$\varepsilon_t = z_t \sigma_t \ \text{ with } z_t \text{ is i.i.d. and } z_t \sim N\left(0, 1\right) \tag{11}$$

where: z_t – series of independently and identically distributed (i.i.d.) random variables with zero mean and unit variance.

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A positive and significant estimate for α_1 indicates that monthly mean returns are larger over the November–April periods, and is taken as the evidence of a significant Halloween effect. We impose $\omega > 0$, $\alpha > 0$, and $\beta > 0$ in order to ensure the conditional variance (σ_t^2) is positive. If $\alpha + \beta < 1$, then the process ε_t is covariance stationary. Previous research show, that the GARCH (1, 1) model is a robust version of this family of models for estimating volatility (Rosini and Shenai 2020).

As more recent studies on the Halloween effect postulate that this anomaly can be driven by the 'January effect' (Haggard and Witte 2010), we replace Equation (9) with the following equation:

$$r_t = \mu + \alpha_1 S_t + \beta_1 J_t + \varepsilon_t \tag{12}$$

where: J_t – indicator, which has a value of 1 in January and 0 otherwise; S_t – dummy variable adjusted by giving the value 1 in the period November to April, except in January.

In order to make all calculations, we use the open-source GRETL 2021b software.

The methodology presented above is employed to verify the following research hypotheses:

H_1: Soft commodities winter and summer returns differ significantly (i.e. the Halloween effect is significant).

H_2: Soft commodities returns exhibit autoregressive conditional heteroscedasticity.

H_3: The Halloween effect in soft commodities markets is driven by the January effect.

First hypothesis (H_1) corresponds to the hypotheses tested by Arendas (2017) and by Burakov and Freidin (2018). Two other hypotheses (H_2 and H_3) are original and to the best of our knowledge, they were not verified in any of the previous studies on the Halloween effect in soft commodities markets.

RESULTS AND DISCUSSION

In Tables 1–2, there are given the estimates of basic distributional characteristics and results of the JB test for summer and winter soft commodities returns.

Descriptive statistics reported in Tables 1–2 reveal important findings. First of all, we can notice that almost all soft commodities exhibit positive mean returns in the winter period (the highest one – cotton). The only exception is sugar with negative winter mean return. Three out of six soft commodities exhibit negative mean returns in the summer period (coffee, cocoa and cotton). Rubber summer mean return, although positive, is lower than the winter mean return. On the contrary, orange juice and sugar summer mean returns are higher than winter returns. Those relationships are illustrated in Figure 1.

Table 1. Descriptive statistics for the summer period returns

Commodity	Average	SD	Kurtosis	Skewness	Minimum	Maximum	JB
Coffee	–0.0024	0.0663	–0.2744	0.1502	–0.1657	0.1659	0.970
Cocoa	–0.0014	0.0582	0.4070	–0.6641	–0.1770	0.1313	9.661*
Sugar	0.0187	0.0862	–0.2692	0.1919	–0.2025	0.2229	1.246
Cotton	–0.0079	0.0751	1.8376	–0.5266	–0.2958	0.1749	21.186*
Frozen orange juice	0.0017	0.0704	1.4045	–0.3716	–0.2705	0.1700	11.731*
Rubber	0.0014	0.0767	5.0951	–0.9022	–0.3968	0.1999	140.071*

*Rejection of null hypothesis at 0.05 level; JB – Jarque-Bera statistic

Source: Own calculations based on Bloomberg (2020) database

Table 2. Descriptive statistics for the winter period returns

Commodity	Average	SD	Kurtosis	Skewness	Minimum	Maximum	JB
Coffee	0.0034	0.0759	0.7191	0.7636	–0.1455	0.2687	14.129*
Cocoa	0.0093	0.0680	1.6477	0.1256	–0.2250	0.2109	12.707*
Sugar	–0.0129	0.0768	1.9783	–0.4284	–0.3234	0.1647	21.797*
Cotton	0.0100	0.0610	0.6331	–0.0197	–0.1653	0.2068	1.660
Frozen orange juice	0.0004	0.0647	0.0402	–0.2078	–0.1954	0.1509	0.886
Rubber	0.0050	0.0776	1.5710	–0.5603	–0.3053	0.1630	17.659*

*Rejection of null hypothesis at 0.05 level; JB – Jarque-Bera statistic

Source: Own calculations based on Bloomberg (2020) database

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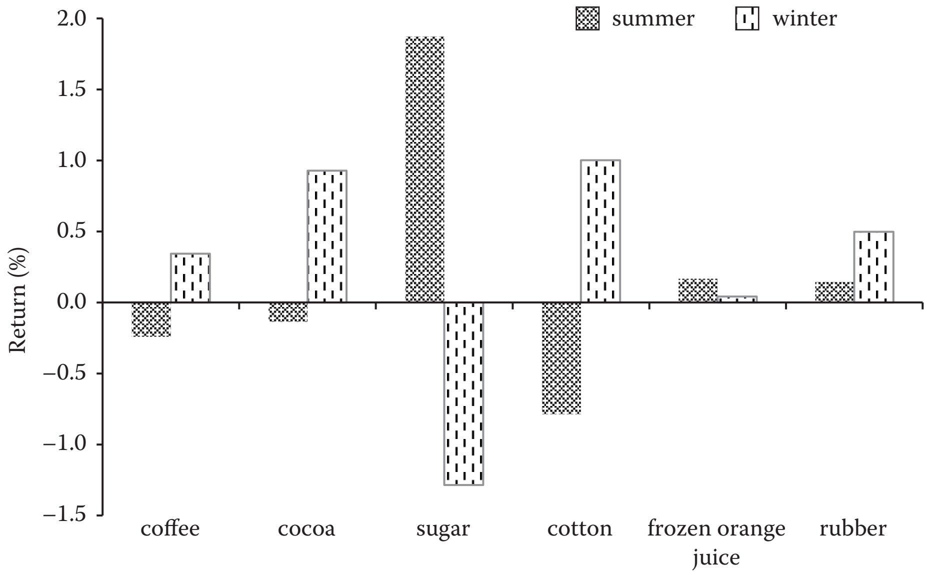

Figure 1. Average returns for the particular time periods (summer and winter)

Source: Own calculations based on Bloomberg (2020) database

Table 3. Two-sample t-test results for winter and summer soft commodities returns

Commodity	t-statistic
Coffee	−0.6507
Cocoa	−1.3353
Sugar	3.0718*
Cotton	−2.0750*
Frozen orange juice	0.1471
Rubber	−0.3634

*Rejection of null hypothesis at 0.05 level
Source: Own calculations based on Bloomberg (2020) database

Table 4. Wilcoxon test results for winter and summer soft commodities returns

Commodity	z-statistic
Coffee	−0.0830
Cocoa	−0.9178
Sugar	2.7759*
Cotton	−2.0379*
Frozen orange juice	0.1296
Rubber	−0.5358

*Rejection of null hypothesis at 0.05 level
Source: Own calculations based on Bloomberg (2020) database

Generally, higher returns are accompanied by higher risk (greater values of SD). Regardless of the period (summer/winter) coffee exhibits positive skewness, whereas cotton, frozen concentrated orange juice and rubber are characterised by negative skewness. Kurtosis for summer rubber returns is higher than 3, so the distribution is leptokurtic. Finally, the JB statistic of normality suggests the rejection of the null hypothesis for almost all returns series.

As Figure 1 suggests the presence of the Halloween effect for four out of six soft commodities (cocoa, coffee, cotton and rubber) and the reverse Halloween effect for sugar and orange juice, to verify the significance we perform the two-sample t-test and the Wilcoxon rank-sum test. The results are given in Tables 3 and 4, respectively.

Although the two-sample t-test is more accurate for the normally distributed data and the Wilcoxon rank-sum test is more accurate for the data that do not follow a normal distribution, the results reported in Tables 3–4 are consistent. The only significant effects are: the Halloween effect for cotton and the reverse Halloween effect for sugar.

In the next step of the research, we test the presence of ARCH effects in our data (Table 5). For all commodities, we can reject the null hypothesis at the first lag

Table 5. ARCH(q) test for soft commodities returns

Commodity	Number of lags (q)		
	1	3	6
Coffee	5.49*	5.64	6.43
Cocoa	4.15*	4.72	5.78
Sugar	5.35*	5.56	9.40
Cotton	5.54*	10.51*	17.80*
Frozen orange juice	4.60*	5.42	6.27
Rubber	6.28*	32.25*	33.87*

*Rejection of null hypothesis at 0.05 level; ARCH – autoregressive conditional heteroskedasticity
Source: Own calculations based on Bloomberg (2020) database

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and for cotton and rubber also at the third and sixth lags at 0.05 level of significance.

First, we estimate GARCH (1, 1) models with dummy variable S_t representing the Halloween effect. The results are given in Table 6.

The estimates of GARCH (1, 1) models given in Table 6 confirm the significance of the Halloween effect for cotton and the reverse Halloween effect for sugar. As it is believed that the Halloween effect may be driven by the January effect, we compute the monthly average returns, displayed in Figure 2. Indeed, these results show that the highest monthly return was observed in January. Thus, to control the January effect, we estimate the GARCH (1, 1) model with the second dummy variable J_t. Results are reported in Table 7.

Results displayed in Table 7 show that including the January dummy does not influence the significance of the reverse Halloween effect observed for sugar. In the case of cotton, the coefficient on the Halloween indicator remains positive but loses significance, however it is still significant at the 10% level as well as the coefficient on January effect. The significant January ef-

Table 6. Estimates of GARCH (1, 1) model with the Halloween effect dummy

Parameter	Commodity					
	coffee	cocoa	sugar	cotton	frozen orange juice	rubber
μ	−0.00281	−0.00050	0.01691	−0.00476	0.00151	0.00252
α_1	0.00471	0.00671	−0.03101*	0.01750*	−0.00010	0.00118
ω	0.00472	0.00017	0.00212	0.00089	0.00058	0.00186*
α	0.05668	0.05525	0.10025	0.25089	0.11953*	0.22286*
β	1.005e−012	0.90410*	0.58148	0.57233*	0.75558*	0.47204

*Significance at 0.05 level; GARCH – generalised autoregressive conditional heteroskedasticity
Source: Own calculations based on Bloomberg (2020) database

Table 7. Estimates of GARCH (1, 1) model with the Halloween effect and January effect dummies

Parameter	Commodity					
	coffee	cocoa	sugar	cotton	frozen orange juice	rubber
μ	−0.00293	−0.00061	0.01704*	−0.00513	0.00147	0.00227
α_1	−0.00120	0.00481	−0.03604*	0.01564	0.00715	−0.00495
β_1	0.03069	0.01787	−0.00556	0.02617	−0.03499*	0.03205*
ω	0.00395	0.00017	0.00207	0.00084	0.00047	0.00180*
α	0.07250	0.05144	0.07769	0.22349	0.12102*	0.22179*
β	0.12982	0.90609	0.60545	0.60592*	0.77209*	0.47619*

*Significance at 0.05 level; GARCH – generalised autoregressive conditional heteroskedasticity
Source: Own calculations based on Bloomberg (2020) database

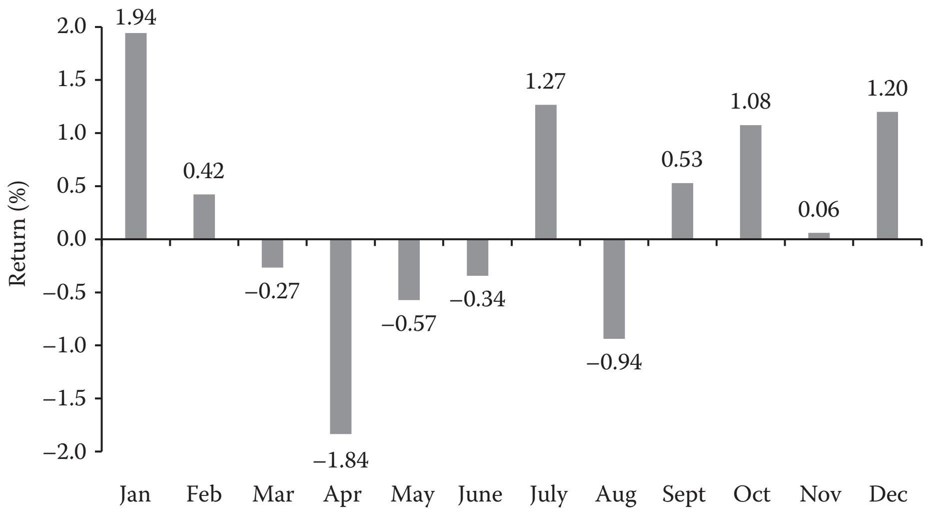

Figure 2. Average monthly returns per month based on six soft commodities

Source: Own calculations based on Bloomberg (2020) database

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fect at 5% level is observed for rubber. Finally, the coefficient estimated for the January effect is negative for orange juice which contradicts the hypothesis that this market exhibit a January effect.

CONCLUSION

According to the EMH proposed by Fama (1965), the stock prices always reflect all of the relevant information. As a consequence, it is impossible to obtain untypical returns when applying technical and fundamental analysis. Nevertheless, numerous papers question the market efficiency proving that some stock returns patterns are related to certain calendar periods. These patterns are called calendar effects. They are, for example, the January effect, turn of the month effect or Halloween effect. These calendar anomalies may be employed in investment strategies that allow obtaining abnormal returns. Taking into account low transaction costs and simple trading rules, the Halloween effect appears to be a remarkable phenomenon.

This paper was aimed at examining the Halloween effect in the markets of basic soft commodities (cocoa, coffee, cotton, frozen concentrated orange juice, rubber and sugar) from October 1999 to October 2020. It contributes to the existing literature in several ways. First, we analyse a dataset covering the last two decades. This long-time span ensures the credibility of results. Second, in contrast to previous studies (Borowski 2015c, Arendas 2017, Burakov and Freidin 2018), we perform not only the two-sample *t*-test and the rank-sum Wilcoxon test. The investigation of the ARCH effect and confirming its presence in our data allows us to estimate GARCH (1, 1) models with a dummy variable representing the Halloween effect. Finally, we also investigate the impact of the January effect on the Halloween effect.

Estimated values of basic descriptive statistics revealed the differences between the average summer period and winter period returns. Both, the two-sample *t*-test and the rank-sum Wilcoxon test suggested a rejection of the null hypothesis for two out of six soft commodities indicating the significant Halloween effect for cotton and the significant reverse Halloween effect for sugar. Estimated GARCH (1, 1) models with the Halloween dummy variable confirmed these findings. Introducing a second dummy variable – the January indicator did not change the results for sugar but reduced the significance of the Halloween effect for cotton.

To sum up, we may state that the first of the hypotheses under consideration (soft commodities winter and summer returns differ significantly, i.e. the Halloween effect is significant) was positively verified and can be accepted only in the case of cotton. The second hypothesis (soft commodities returns exhibit autoregressive conditional heteroscedasticity) can be fully accepted. The last hypothesis (the Halloween effect in soft commodities markets is driven by the January effect) was confirmed in the case of cotton – the only commodity exhibiting the Halloween effect. Our results confirm the findings of Arendas (2017) and Burakov and Freidin (2018) who also detected the significant Halloween effect for cotton. On the contrary, they reported the insignificant reverse Halloween effect for sugar.

In the consequence of confirming the Halloween effect in the market of cotton, the reverse Halloween effect in the market of sugar and the January effect in markets of orange juice and rubber we get the evidence for the weakness of the EMH. This brings implications that could be useful to professional and retail investors, market regulators, and agribusiness enterprises producing and/or processing these soft commodities within their business activities, as well to importers and exporters interested in the performance of these markets. Based on the knowledge, they may apply different trading strategies allowing them to obtain satisfactory (abnormal) profits or they can use derivatives (futures or options) for hedging against unfavourable changes in soft commodities prices. As this paper was limited to investigating only one of the seasonal anomalies, in future work other calendar effects (such as the weekday effect, the month of the year effect, turn of the month effect or the holidays effect) could be examined.

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