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Analysis of Seasonal Patterns in the Performance of Fuel Markets in the Visegrad Group

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Abstract

The objective of the paper is to examine seasonal patterns in the performance of fuel markets in the Visegrad Group (V4) countries (i.e., the Czech Republic, Hungary, Poland, and Slovakia). Unlike numerous papers that investigate global oil markets, this study focuses on regional retail fuel markets. The dataset consists of weekly Pb95 gasoline and diesel prices from January 2016 through December 2020. The methods applied cover a range of statistical and econometric tools, such as the Wilcoxon rank sum test, simple regression, and the generalized autoregressive conditional heteroscedasticity (GARCH) models. The research refers to important calendar effects such as the month-of-the-year effect and the Halloween effect, but it also considers the seasonal gasoline transition effect. The empirical analysis presented in this paper does not bring clear evidence for significant seasonal patterns in the performance of fuel markets in the Visegrad Group as the application of different methods provides mixed results. Nevertheless, the findings of the Wilcoxon test are consistent with the GARCH (1, 1) estimates, which detected an April effect for gasoline and a December effect for diesel in Poland. The simple regression and GARCH (1, 1) estimates are consistent for an October effect for gasoline in Slovakia. None of the methods applied allows us to find a significant Halloween effect, a reverse Halloween effect, or a gasoline seasonal transition effect on the fuel markets of the Visegrad Group. These findings bring new insight into the V4 fuel markets and may be important for oil processing firms, retail traders, transport and distribution companies, farmers, and individual consumers.

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Introduction

Gasoline retail markets have traditionally attracted a lot of attention from policymakers, producers, retail traders and consumers, but also from researchers. There are many contributing factors that impact fuel prices, such as the exterior costs of oil, fuel companies' margins, or natural disasters (like hurricanes), which can increase prices by disrupting transport routes or damaging refineries and other infrastructure. The currency market has an impact, too. Alongside economic conditions, there is another factor behind the alterations in price – the season. Research conducted by the Association for Convenience and Fuel Retailing (NACS) in the U.S. explained that prices in North America tend to go up in spring, starting around Memorial Day (the last Monday in May).

There are many reasons behind the increase in summer fuel prices. First, more people are traveling; in particular, families tend to take vacations and other trips during the summer, which increases demand and results in higher prices. Next, in the spring months, energy companies conduct maintenance of their refineries, shutting them down and limiting capacity until late May. Finally, twice every year, the fuel supply in the United States changes. This operation is known as the seasonal gasoline transition (Howstuffworks b.r.).

In warmer months, gasoline has a greater risk of evaporating from cars' fuel systems, generating additional smog and increased emissions. In order to reduce pollution, refiners produce summer-blend fuels that have lower Reid vapor pressure (RVP) or lower volatility. These blends burn cleaner and also help compensate for the limited oil supply, but they are more expensive. Refineries switch over to summer-blend production in March and April; fuel terminals are required to sell only summer gasoline from May 1, while gasoline stations must complete the changeover to summer gasoline by June 1. In winter, gasoline blends have a higher Reid vapor pressure that makes them evaporate more easily and allows gasoline to ignite more easily in cold temperatures. This blend is cheaper to produce, which results in lower gas prices at gasoline stations from late September through late April (GasBuddy b.r.).

Diesel fuel also exhibits some seasonality, but the effect is smaller. At one time, diesel prices were correlated to the heating oil market, which meant higher diesel prices in winter. This is no longer the case as large equipment and truck use dominate the diesel market. However, in winter, prices for diesel fuel are usually lower than during the rest of the year (Ibendhal 2019).

According to the U.S. Energy Information Administration (U.S. Energy Information Administration b.r.), crude oil is the largest component of the retail price of gasoline. Some recent studies indicate there are certain seasonal patterns in oil price behavior. These patterns are referred to as calendar anomalies. The best recognized are the day-of-the-week, the month-of-the-year, the turn-of-the-month, and the Halloween effects. For example, Yu and Shih (2011) investigated the West Texas Intermediate (WTI) daily closing spot prices of crude oil from 1986 through 2007 and found a positive Wednesday effect. Górska and Krawiec (2015) analyzed daily closing prices of crude oil from WTI and Brent from 2000 through 2014 and revealed significantly different returns on Monday and Friday and significantly different returns in February. Borowski (2016) examined crude oil futures contracts quoted on the New York Mercantile Exchange from 1983 through 2016 and discovered significantly different returns in November as well on Thursday and Friday. Burakov, Freidin, and Solovyev (2018) explored monthly closing prices of crude oil from 1985 through 2016 and reported a significant Halloween effect. Arendas, Tkacova, and Bukoven (2018) investigated Brent and WTI monthly prices from 1983 through 2017 and showed abnormal positive returns in March, April, and August and abnormal negative returns in October and November.

To the best of our knowledge, relatively little work has been done to examine calendar effects in fuel retail markets. For example, Valadkhani (2013) used daily retail prices of unleaded petrol in 114 locations across Australia from January 2005 to April 2012 to search for the day-of-the-week effect. He observed that prices mostly peaked on Thursday/Friday and then declined until they hit their cyclical lowest prices, mainly on Sunday/Tuesday. However, these daily differences were only statistically significant in capital cities or large regional centers. Rosado, Guerra, and Ferreira (2020) employed gasoline and diesel total daily sales in liters from January 2001 through 2018 in Portalegre (Portugal). They explored seasonality between morning and afternoon shifts, as well as the seasonality on weekdays and in months. They found significantly higher sales of gasoline in the afternoon, and significantly higher sales of diesel in the morning. Next, the analysis of weekdays allowed them to state that, in several cases, the sales were higher at the end of the season than at the beginning (although diesel exhibited different behavior). Moreover, the highest sales were observed on Friday. Finally, their analysis of monthly seasonality revealed that December and October seemed to be the best months for sales.

This paper examines seasonal patterns in the performance of fuel markets in the Visegrad Group (V4) countries (the Czech Republic, Hungary, Poland, and Slovakia) from January 2016 through December 2020. The Visegrad Group was established in 1991. The V4 countries cooperate in various areas of systemic reforms and social changes, science and education, culture, regional development, security, and in the area of energy and transport (Ambroziak et al. 2020). As the dataset used for the research covers gasoline Pb95 and diesel fuel weekly prices, it makes analyzing weekday effects impossible. That is why we focus on examining the month-of-the-year and the Halloween effects. The month-of-the-year effect holds that returns expected on traded assets differ statistically by the month of the year. Empirical studies have documented that stock market returns are often much higher in January than in other months; this effect is commonly known as the January effect. Other monthly effects are the May effect (low returns) and the September effect (high returns). The Halloween effect is an anomaly in which the months of November through April provide higher returns than the remaining months of the year.

The paper contributes to the existing literature in several ways. First of all, in contrast to the majority of papers that examine calendar effects on global oil markets, we focus on regional retail fuel markets. Next, to search for calendar effects, we apply a range of different methods, including the Wilcoxon rank sum test, simple regression, and generalized autoregressive conditional heteroscedasticity (GARCH) models. Finally, we check whether the seasonal gasoline transition effect observed in the U.S. market is also present in the Visegrad Group. The paper is organized as follows. The next two sections present the methodology and the detailed results. The last section offers concluding remarks.

Methodology

Two-sample t-test

The simplest way to detect calendar effects is to run the two-sample *t*-test and to verify

$H_0\colon E(r_1) = E(r_2)$

against

$H_1\colon E(r_1) \neq E(r_2)$.

The test statistic is given by (Osińska 2006):

$$t = \frac{\bar{r}_1 - \bar{r}_2}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}}, \tag{1}$$

where $\bar{r}_1$ is the arithmetic mean calculated for sample 1 (for example, January returns),

$\bar{r}_2$ is the arithmetic mean calculated for sample 2 (for example, February returns),

S_1^2 is the variance calculated for the first sample (January returns),

S_2^2 is the variance calculated for the second sample (February returns), and n_1 and n_2 are the numbers of observations, respectively, in the first and the second samples. For large samples, the t-statistic follows the normal distribution.

Wilcoxon rank sum test

It often happens that commodity returns do not follow a normal distribution, so instead of the two-sample t-test, the non-parametric Wilcoxon rank sum test can be used to verify whether the returns differ significantly. The Wilcoxon rank sum test allows us to compare two distributions without having to make assumptions about the nature of distributions, whether normal or not. In special cases, both distributions are identical in terms of shape and dispersion, differing only in the median value. This test is much less sensitive to outliers than the two-sample t-test, and it reacts to other differences between the distributions, such as differences in shape. When the assumptions of the two-sample t-test hold, the Wilcoxon rank sum test is somewhat less likely to detect a location shift than the two-sample t-test. However, the losses in this regard are usually quite small (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 2. The Wilcoxon test is based on 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 (w_1). For larger samples (n > 10), we can use the boundary normal distribution N(μ_1, σ_1), where:

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

and

$$\sigma_1 = \sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}}. \tag{3}$$

The test statistic z is:

$$z = \frac{w_1 - \mu_1}{\sigma_1} \sim N(0,1). \tag{4}$$

Simple regression

To investigate specific month effects, Borges (2009) suggests estimating the simple regression equations:

$$r_t = \beta_0 + \beta_{i1} M_{it} + \varepsilon_t, \tag{5}$$

where

r_t – continuously compounded monthly returns,

β_0, β_1 – model parameters,

ε_t – error term. Here, one needs twelve different dummies: *Mi* (*i* = 1, …, 12). Each takes the value of 1 if the return is of January, February etc., and 0 otherwise. The *t*-test of β_1 tells us if this effect is significant.

Generalized autoregressive conditional heteroscedasticity (GARCH) model

In order to investigate calendar effects, GARCH models may also be applied. Numerous studies show that the GARCH (1, 1) model is a robust version of this family of models for estimating volatility (Rosini and Shenai 2020). However, it is necessary to first perform a test of ARCH effects. The ARCH(q) test proposed by Engle (1982) considers the following model:

$$\varepsilon_t^2 = \lambda_0 + \sum_{i=1}^{q} \lambda_i \varepsilon_{t-1}^2 + \zeta_t \tag{6}$$

and the following null hypothesis:

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

is tested against the alternative hypothesis:

H_1: $\exists_i \lambda_i \neq 0$.

The test statistic LM is:

$$LM = T \cdot R^2, \tag{7}$$

where T denotes the number of observations and R^2 is the coefficient of determination for equation (6). The statistic follows an asymptotic chi-squared distribution with *q* degrees of freedom.

After detecting ARCH effects, one can estimate the following GARCH (1, 1) model with dummy variables:

$$r_t = \sum_{i=1}^{12} b_i M_{it} + \varepsilon_t \text{ with } \varepsilon_t \mid \Omega_{t-1} : N\left(0, \sigma_t^2\right), \tag{8}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2, \tag{9}$$

$$\varepsilon_t = z_t\sigma_t \text{ with } z_t \text{ is i.i.d. and } z_t \sim \mathrm{N}(0, 1). \tag{10}$$

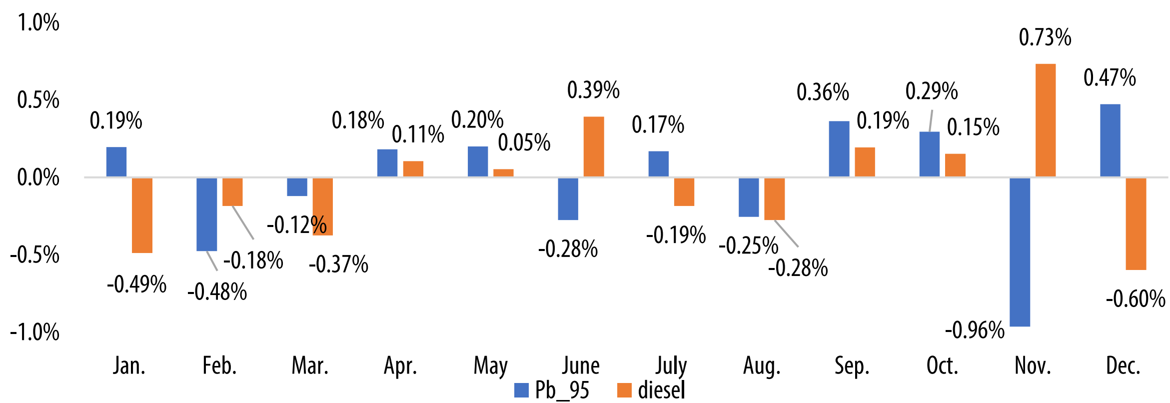
We impose $\omega > 0$, $\alpha > 0$, and $\beta > 0$ to ensure that the conditional variance (σ_t^2) is positive. If $\alpha + \beta < 1$, then the process ε_t is covariance stationary. z_t is a series of independently and identically distributed (i.i.d.) random variables with zero mean and unit variance (Qi and Wang 2013).

Empirical results

The month-of-the-year effect

In the first step of the research, we examine monthly average returns to test for the month-of-the-year effects. Average monthly Pb95 and diesel returns in the Czech Republic, Hungary, Poland and Slovakia from 2016 to 2020 are displayed in Figure 1. They were estimated on the basis of weekly prices (260 observations) expressed in domestic currencies per liter. The original data is provided by e-petrol.pl (n.d.) and published every Wednesday at 3 pm.

(a)



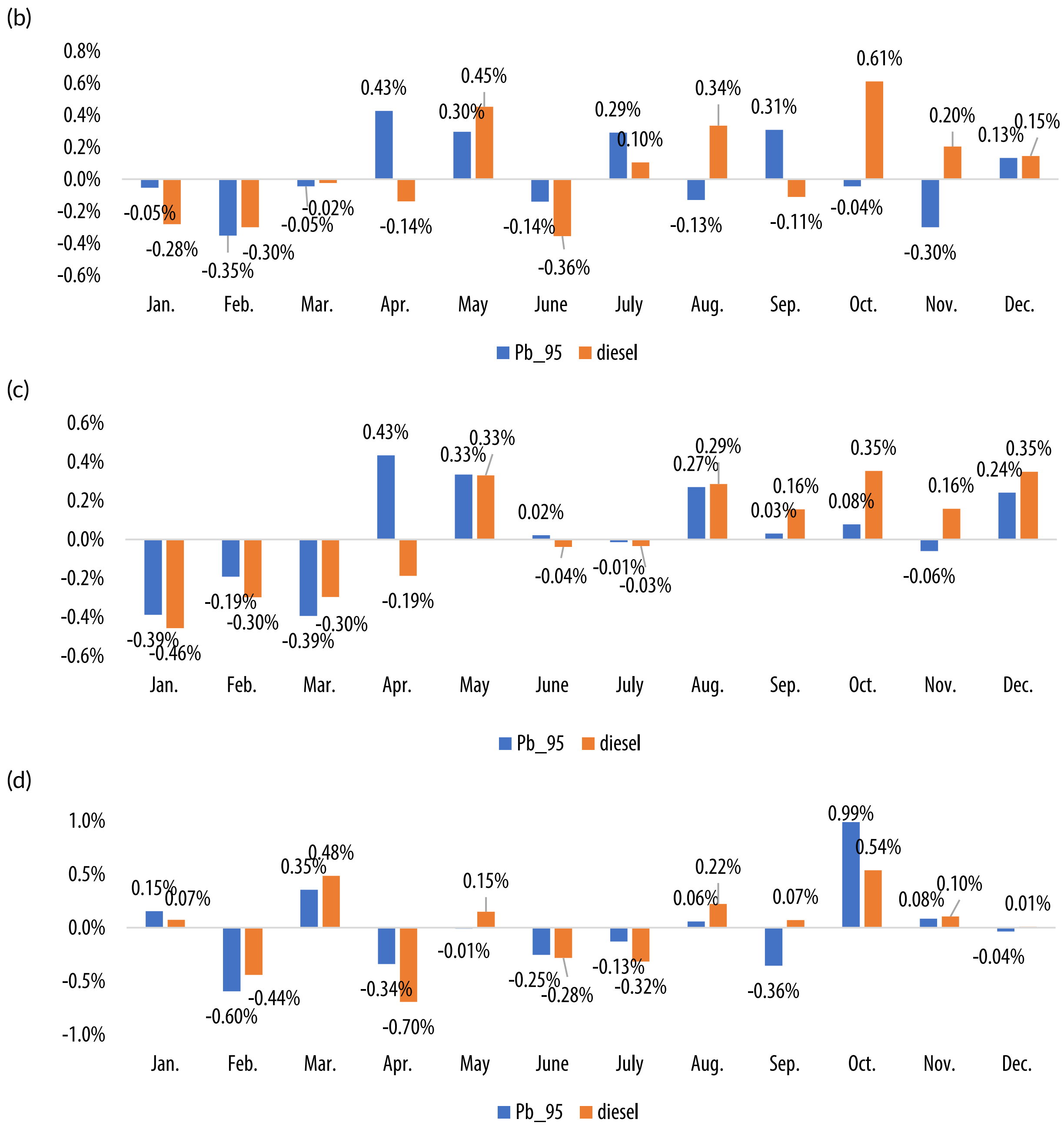


Figure 1. Average monthly Pb95 gasoline and diesel returns in the Czech Republic (a), Hungary (b), Poland (c) and Slovakia (d) from 2016 to 2020

Source: own elaboration based on data provided by e-petrol (n.d.).

For the Czech Republic, Figure 1 reveals positive gasoline average returns in January, April, May, July, September, October, and December, as well as positive diesel average returns in April, May, June, September, October, and November. For Hungary, there are positive gasoline average returns in April, May, July, September, and December and positive diesel average returns in May, July, August, October, November, and December. In Poland, positive gasoline average returns are observed in April, May, June, August, September, October, and December and positive diesel average returns in May, August, September, October, November, and December. Finally, for Slovakia, positive gasoline average returns are reported in January, March, August, October, and November and positive diesel average returns in January, March, May, August, September, October, November, and December. Thus, based on Figure 1, we cannot find patterns in gasoline and diesel monthly average returns that are common for all V4 countries, except negative average gasoline and diesel returns in February and positive average diesel returns in May, October, and November.

Next, for each dataset covering monthly returns, we perform the Shapiro–Wilk normality test[1] to determine which statistical test (the two-sample *t*-test or the Wilcoxon rank sum test) is more robust. The results are reported in Tables 1 and 2. In numerous cases, they suggest rejection of the null hypothesis that the distributions of monthly fuel returns follow a normal distribution, so in our opinion, the Wilcoxon rank sum test is more appropriate for our data. The results of this test are given in Tables 3 and 4.

Table 1. The Shapiro–Wilk test results for Pb95 gasoline monthly returns

Month	Country			
	Czech Rep.	Hungary	Poland	Slovakia
January	0.945 (0.25)	0.906 (0.04)	0.970 (0.70)	0.572 (0.00)
February	0.877 (0.02)	0.794 (0.00)	0.880 (0.02)	0.690 (0.00)
March	0.925 (0.10)	0.929 (0.12)	0.935 (0.16)	0.793 (0.00)
April	0.935 (0.17)	0.935 (0.17)	0.958 (0.48)	0.564 (0.00)
May	0.956 (0.39)	0.879 (0.01)	0.944 (0.22)	0.747 (0.00)
June	0.887 (0.02)	0.757 (0.00)	0.793 (0.00)	0.785 (0.00)
July	0.877 (0.01)	0.969 (0.70)	0.964 (0.58)	0.898 (0.03)
August	0.972 (0.74)	0.948 (0.27)	0.953 (0.34)	0.646 (0.00)
September	0.676 (0.00)	0.967 (0.66)	0.934 (0.16)	0.592 (0.00)

1 This test, proposed by Shapiro and Wilk in 1965, is commonly used for small samples. The null hypothesis of this test is that the population is normally distributed.

Month	Country			
	Czech Rep.	Hungary	Poland	Slovakia
October	0.849 (0.00)	0.945 (0.25)	0.886 (0.02)	0.586 (0.00)
November	0.923 (0.09)	0.955 (0.40)	0.686 (0.00)	0.839 (0.00)
December	0.879 (0.02)	0.896 (0.03)	0.903 (0.04)	0.576 (0.00)

Note: (•) – p-value
Source: own calculations based on data provided by e-petrol (n.d.).

Table 2. The Shapiro–Wilk test results for diesel monthly returns

Month	Country			
	Czech Rep.	Hungary	Poland	Slovakia
January	0.974 (0.80)	0.865 (0.01)	0.949 (0.30)	0.585 (0.00)
February	0.957 (0.49)	0.733 (0.00)	0.960 (0.55)	0.672 (0.00)
March	0.925 (0.10)	0.902 (0.03)	0.914 (0.06)	0.802 (0.00)
April	0.934 (0.17)	0.713 (0.00)	0.961 (0.53)	0.551 (0.00)
May	0.989 (0.99)	0.931 (0.12)	0.916 (0.05)	0.811 (0.00)
June	0.792 (0.00)	0.958 (0.47)	0.773 (0.00)	0.643 (0.00)
July	0.949 (0.30)	0.897 (0.03)	0.977 (0.85)	0.469 (0.00)
August	0.890 (0.02)	0.847 (0.00)	0.931 (0.11)	0.627 (0.00)
September	0.922 (0.09)	0.919 (0.08)	0.864 (0.01)	0.375 (0.00)
October	0.919 (0.07)	0.866 (0.01)	0.961 (0.50)	0.379 (0.00)
November	0.923 (0.09)	0.980 (0.91)	0.879 (0.01)	0.829 (0.00)
December	0.874 (0.01)	0.902 (0.05)	0.897 (0.04)	0.525 (0.00)

Note: (•) – p-value
Source: own calculations based on data provided by e-petrol (n.d.).

Table 3. Monthly effects for Pb95 gasoline – the Wilcoxon rank sum test

Pair	Country			
	Czech Rep.	Hungary	Poland	Slovakia
January – February	– 0.907 (0.37)	– 1.020 (0.31)	0.038 (0.97)	– 0.667 (0.51)
January – March	0.528 (0.60)	0.493 (0.62)	0.070 (0.94)	– 1.033 (0.30)
January – April	– 0.510 (0.61)	0.960 (0.34)	2.235 (0.03)	1.118 (0.26)
January – May	0.068 (0.95)	– 0.920 (0.36)	– 1.567 (0.12)	– 0.341 (0.73)
January – June	– 0.292 (0.77)	– 1.263 (0.21)	0.535 (0.59)	0.340 (0.73)
January – July	– 0.070 (0.94)	– 0.939 (0.35)	– 1.221 (0.22)	0.200 (0.84)
January – August	0.602 (0.55)	0.363 (0.72)	– 2.157 (0.03)	– 0.409 (0.68)
January – September	0.535 (0.59)	0.462 (0.64)	1.361 (0.17)	– 0.510 (0.61)
January – October	– 0.669 (0.50)	0.786 (0.43)	– 1.291 (0.20)	– 1.526 (0.13)
January – November	1.373 (0.17)	0.974 (0.33)	– 1.174 (0.24)	– 0.293 (0.77)
January – December	0.844 (0.40)	0.730 (0.47)	2.405 (0.02)	0.176 (0.86)

Note: (•) – p-value
Source: own calculations based on data provided by e-petrol (n.d.).

Table 4. Monthly effects for diesel – the Wilcoxon rank sum test

Pair	Country			
	Czech Rep.	Hungary	Poland	Slovakia
January – February	– 0.013 (0.99)	0.050 (0.96)	0.113 (0.91)	– 0.113 (0.91)
January – March	– 0.141 (0.89)	– 0.516 (0.61)	– 0.493 (0.62)	– 1.631 (0.10)
January – April	0.097 (0.92)	1.604 (0.11)	0.425 (0.67)	– 0.741 (0.46)
January – May	– 0.454 (0.65)	– 1.453 (0.15)	– 1.419 (0.16)	– 0.795 (0.43)

Pair	Country			
	Czech Rep.	Hungary	Poland	Slovakia
January – June	0.765 (0.44)	– 0.292 (0.77)	0.413 (0.68)	0.389 (0.70)
January – July	– 0.293 (0.77)	– 0.704 (0.48)	– 0.915 (0.36)	0.634 (0.53)
January – August	– 0.182 (0.86)	– 1.135 (0.26)	– 1.555 (0.12)	– 0.284 (0.78)
January – September	0.267 (0.79)	0.413 (0.68)	1.652 (0.10)	0.255 (0.80)
January – October	– 0.634 (0.53)	– 1.948 (0.05)	– 1.878 (0.06)	– 0.657 (0.51)
January – November	– 1.303 (0.19)	– 0.704 (0.48)	– 1.514 (0.13)	– 0.035 (0.97)
January – December	0.063 (0.95)	1.662 (0.10)	2.569 (0.01)	– 0.227 (0.82)

Note: (•) – p-value
Source: own calculations based on data provided by e-petrol (n.d.).

The Wilcoxon rank sum test results show that only in Poland does the average January gasoline return differ significantly from April, August and December's average returns. The average January diesel return is significantly different from the December return (at the 0.05 level).

Next, to investigate individual month-of-the-year effects, we estimate simple regressions. The results for β_{i1} coefficients are set in Tables 5 and 6. They reveal a significant positive October effect for Pb95 gasoline in Slovakia and a significant negative April effect for diesel in Slovakia (at the 0.05 level).

Table 5. Monthly effects for Pb95 gasoline – simple regression

Month	Country			
	Czech Rep.	Hungary	Poland	Slovakia
January	0.0036 (0.52)	– 0.0002 (0.95)	– 0.0039 (0.17)	0.0023 (0.58)
February	– 0.0051 (0.39)	– 0.0043 (0.26)	– 0.0025 (0.40)	– 0.0064 (0.15)
March	– 0.0013 (0.82)	– 0.0010 (0.79)	– 0.0042 (0.13)	0.0038 (0.37)
April	0.0011 (0.86)	0.0028 (0.46)	0.0031 (0.29)	– 0.0053 (0.22)

Month	Country			
	Czech Rep.	Hungary	Poland	Slovakia
May	0.0024 (0.67)	0.0029 (0.42)	0.0031 (0.27)	0.0006 (0.88)
June	–0.0027 (0.64)	–0.0020 (0.60)	0.00004 (0.99)	–0.0023 (0.59)
July	0.0020 (0.73)	0.0033 (0.36)	–0.0005 (0.87)	–0.0017 (0.68)
August	–0.0025 (0.65)	–0.0017 (0.64)	0.0026 (0.35)	0.0009 (0.833)
September	0.0038 (0.51)	0.0028 (0.46)	0.0001 (0.98)	–0.0036 (0.40)
October	0.0034 (0.55)	–0.0013 (0.72)	0.0002 (0.93)	0.0101 (0.02)
November	–0.0101 (0.07)	–0.0033 (0.37)	–0.0010 (0.73)	0.0008 (0.85)
December	0.0055 (0.35)	0.0020 (0.61)	0.0030 (0.31)	–0.0003 (0.94)

Note: (•) – p-value
Source: own calculations based on data provided by e-petrol (n.d.).

Table 6. Monthly effects for diesel – simple regression

Month	Country			
	Czech Rep.	Hungary	Poland	Slovakia
January	–0.0036 (0.63)	–0.002 (0.54)	–0.0041 (0.10)	0.0015 (0.71)
February	–0.0018 (0.82)	–0.004 (0.30)	–0.0037 (0.16)	–0.0048 (0.23)
March	–0.0040 (0.60)	–0.001 (0.79)	–0.0031 (0.22)	0.0054 (0.17)
April	0.0006 (0.93)	–0.003 (0.39)	–0.0034 (0.19)	–0.0087 (0.03)
May	0.0011 (0.88)	0.0041 (0.27)	0.0029 (0.24)	0.0019 (0.63)
June	0.0047 (0.55)	–0.0044 (0.26)	0.0005 (0.85)	–0.0025 (0.53)
July	–0.0016 (0.84)	0.0006 (0.87)	–0.0009 (0.73)	–0.0037 (0.34)
August	–0.0032 (0.67)	0.0027 (0.47)	0.0027 (0.28)	0.0026 (0.49)

Month	Country			
	Czech Rep.	Hungary	Poland	Slovakia
September	0.0019 (0.80)	–0.0021 (0.57)	0.0011 (0.67)	0.0007 (0.86)
October	0.0021 (0.79)	0.0055 (0.14)	0.0032 (0.20)	0.0054 (0.17)
November	0.0090 (0.24)	0.0014 (0.71)	0.0012 (0.34)	0.0013 (0.73)
December	–0.0054 (0.49)	0.0022 (0.58)	0.0042 (0.11)	0.0001 (0.99)

Note: (•) – p-value
Source: own calculations based on data provided by e-petrol (n.d.).

In the next stage of the research, we test the presence of ARCH effects in the data. The results are given in Table 7. Regardless of the number of lags, we cannot reject the null hypothesis for diesel in Slovakia, so there is no reason to estimate GARCH models based on the data. Moreover, in the case of Pb95 gasoline returns in the Czech Republic, matrix was not positive definite. Thus, Table 8 presents GARCH (1, 1) estimates for gasoline returns in Hungary, Poland, and Slovakia and diesel returns in the Czech Republic, Hungary, and Poland.

Table 7. ARCH(q) test for Pb95 gasoline and diesel

Fuel	q		
	1	4	12
Czech Rep. Pb95	1.18 (0.27)	11.89 (0.02)	24.77 (0.02)
Hungary Pb95	1.68 (0.19)	8.22 (0.08)	31.59 (0.00)
Poland Pb95	29.55 (0.00)	35.23 (0.00)	35.18 (0.00)
Slovakia Pb95	0.59 (0.44)	12.26 (0.02)	14.85 (0.24)
Czech Rep. diesel	8.68 (0.003)	86.42 (0.00)	20.18 (0.06)
Hungary diesel	12.92 (0.00)	13.13 (0.01)	16.69 (0.16)
Poland diesel	10.14 (0.00)	14.59 (0.01)	24.93 (0.01)

Fuel	q		
	1	4	12
Slovakia diesel	0.01 (0.94)	1.03 (0.91)	2.33 (0.99)

Note: (•) – p-value
Source: own calculations based on data provided by e-petrol (n.d.).

Table 8. Monthly effects for Pb95 gasoline and diesel – GARCH (1, 1) approach

Estimate	Hungary Pb95	Poland Pb95	Slovakia Pb95	Czech Rep. diesel	Hungary diesel	Poland diesel
b_1	0.0015 (0.64)	-0.0020 (0.19)	0.0027 (0.43)	0.0047 (0.50)	-0.00002 (0.99)	-0.0012 (0.48)
b_2	-0.0058 (0.10)	0.0009 (0.60)	-0.0057 (0.12)	-0.0020 (0.69)	-0.0030 (0.39)	-0.0023 (0.11)
b_3	0.0029 (0.44)	0.0051 (0.01)	0.0046 (0.23)	-0.0026 (0.50)	0.0002 (0.96)	0.0083 (0.00)
b_4	0.0090 (0.44)	0.0095 (0.00)	-0.0010 (0.81)	0.0021 (0.72)	0.0022 (0.52)	0.0022 (0.35)
b_5	0.0061 (0.01)	0.0073 (0.00)	0.0032 (0.40)	0.00003 (0.99)	0.0088 (0.01)	0.0060 (0.00)
b_6	-0.0037 (0.29)	-0.0019 (0.34)	0.0024 (0.63)	0.0191 (0.00)	-0.0035 (0.34)	-0.0023 (0.37)
b_7	0.0023 (0.48)	-0.0022 (0.22)	-0.0046 (0.20)	0.0042 (0.41)	0.0013 (0.71)	0.0006 (0.77)
b_8	-0.0009 (0.74)	0.0027 (0.15)	0.0009 (0.78)	0.0052 (0.36)	0.0065 (0.03)	0.0049 (0.02)
b_9	0.0032 (0.27)	0.0001 (0.96)	-0.0034 (0.34)	-0.0005 (0.92)	-0.0006 (0.85)	0.0015 (0.31)
b_{10}	-0.0013 (0.69)	-0.0034 (0.00)	0.0096 (0.02)	0.0020 (0.61)	0.0079 (0.01)	0.0029 (0.13)
b_{11}	-0.0020 (0.53)	0.0013 (0.34)	0.0005 (0.89)	-0.0003 (0.94)	0.0020 (0.51)	0.0020 (0.16)
b_{12}	0.0033 (0.30)	0.0033 (0.05)	-0.0010 (0.79)	0.0056 (0.23)	0.0036 (0.27)	0.0070 (0.00)
$\hat{\omega}$	0.00004 (0.01)	0.00001 (0.02)	0.0001 (0.01)	0.0003 (0.02)	0.0002 (0.00)	0.00003 (0.00)
$\hat{\alpha}$	0.1244 (0.01)	0.5569 (0.00)	0.1078 (0.03)	0.5804 (0.00)	0.3004 (0.00)	0.7026 (0.00)

Estimate	Hungary Pb95	Poland Pb95	Slovakia Pb95	Czech Rep. diesel	Hungary diesel	Poland diesel
$\hat{\beta}$	0.7174 (0.00)	0.4431 (0.00)	0.6929 (0.00)	0.2681 (0.08)	0.0954 (0.35)	0.1679 (0.03)

Note: (•) – p-value
Source: own calculations based on data provided by e-petrol (n.d.).

The results reported in Table 8 reveal several monthly effects that are significant at the 0.05 level: the March effect for gasoline and diesel in Poland, the April effect for gasoline in Poland, the May effect for gasoline and diesel in Hungary and Poland, the June effect for diesel in the Czech Republic, the August effect for diesel in Hungary and Poland, the October effect for gasoline in Poland and Slovakia, and diesel in Hungary, and the December effect for diesel in Poland. All these estimates are statistically significantly positive, except for the October average monthly gasoline return in Poland.

The Halloween effect

The second part of the research investigates the Halloween effect. Following Bouman and Jacobsen (2002), who were the first to describe this effect, we define two separate periods: winter (November to April) and summer (May to October). Average returns for these particular periods are displayed in Figure 2.

Figure 2 shows positive average summer gasoline and diesel returns in all countries and negative winter returns. It suggests the reverse Halloween effect. Before examining this effect, we performed the Shapiro–Wilk test. Table 9 provides the results. This time, they suggest the rejection of the null hypothesis in all cases. Thus, in the next step, we perform the Wilcoxon rank sum test (the results are reported in Table 10).

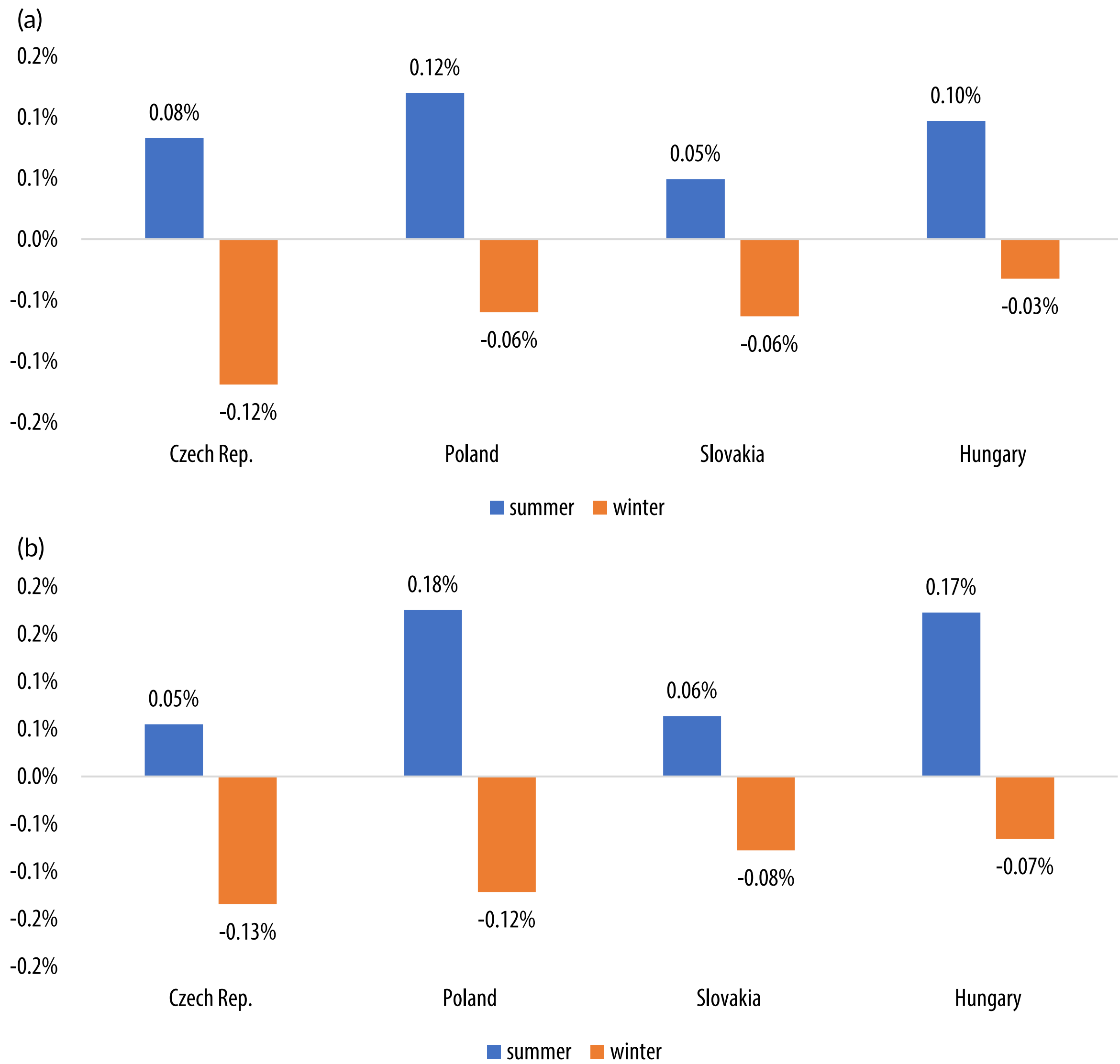


Figure 2. Average returns for particular periods (summer and winter) in the Czech Republic, Hungary, Poland and Slovakia from 2016 to 2020: Pb95 (a) and diesel (b)

Source: own elaboration based on data provided by e-petrol (n.d.).

Table 9. The Shapiro–Wilk test for particular periods (winter and summer)

Period	Czech Rep. Pb95	Hungary Pb95	Poland Pb95	Slovakia Pb95	Czech Rep. diesel	Hungary diesel	Poland diesel	Slovakia diesel
Winter	0.967 (0.00)	0.939 (0.00)	0.861 (0.00)	0.686 (0.00)	0.920 (0.00)	0.890 (0.00)	0.927 (0.00)	0.687 (0.00)
Summer	0.921 (0.00)	0.913 (0.00)	0.949 (0.00)	0.741 (0.00)	0.890 (0.00)	0.889 (0.00)	0.926 (0.00)	0.511 (0.00)

Note: (•) – p-value
Source: own calculations based on data provided by e-petrol (n.d.).

Table 10. The Halloween effect – the Wilcoxon rank sum test

Fuel	Czech Rep. Pb95	Hungary Pb95	Poland Pb95	Slovakia Pb95	Czech Rep. diesel	Hungary diesel	Poland diesel	Slovakia diesel
z	−1.146 (0.25)	−0.159 (0.87)	−0.806 (0.42)	−0.017 (0.99)	−0.299 (0.77)	−0.342 (0.73)	−1.397 (0.16)	−0.351 (0.73)

Note: (•) – p-value
Source: own calculations based on data provided by e-petrol (n.d.).

The results given in Table 10 do not reveal any significant differences between summer and winter gasoline and diesel returns, so they detect neither Halloween nor reverse Halloween effects.

Next, we estimate simple regressions with the redefined seasonal dummy variable in equation (5), which now takes the value of 1 if month t falls in the November–April period and 0 otherwise. The results are reported in Table 11. They also do not find any significant effects.

Table 11. The Halloween effect – simple regression

Period	Czech Rep. Pb95	Hungary Pb95	Poland Pb95	Slovakia Pb95	Czech Rep. diesel	Hungary diesel	Poland diesel	Slovakia diesel
Winter	−0.0020 (0.53)	−0.0013 (0.54)	−0.0018 (0.27)	−0.0013 (0.58)	−0.0015 (0.73)	−0.0021 (0.31)	−0.0027 (0.05)	−0.0014 (0.51)

Note: (•) – p-value
Source: own calculations based on data provided by e-petrol (n.d.).

Finally, we estimate GARCH (1, 1) models, with the Halloween effect seasonal dummy and constant. The results provided in Table 12 do not reveal significant effects.

Table 12. The Halloween effect – GARCH (1, 1) approach

Estimate	Hungary Pb95	Poland Pb95	Czech Rep. diesel	Hungary diesel	Poland diesel
Const.	0.0009 (0.50)	−0.0011 (0.15)	0.0025 (0.26)	0.0035 (0.02)	0.0021 (0.03)
b_1	0.0001 (0.96)	0.0038 (0.07)	−0.0021 (0.50)	−0.0028 (0.17)	−0.0013 (0.35)
$\hat{\omega}$	0.00004 (0.02)	0.00001 (0.17)	0.0003 (0.02)	0.0002 (0.00)	0.0001 (0.00)
$\hat{\alpha}$	0.0827 (0.03)	0.4556 (0.00)	0.4028 (0.00)	0.2470 (0.01)	0.2891 (0.01)

Estimate	Hungary Pb95	Poland Pb95	Czech Rep. diesel	Hungary diesel	Poland diesel
$\hat{\beta}$	0.7620 (0.00)	0.5444 (0.00)	0.3365 (0.03)	0.1030 (0.31)	0.2271 (0.10)

Note: (•) – p-value
Source: own calculations based on data provided by e-petrol (n.d.).

Seasonal gasoline transition effect

The last part of the research aims to ascertain whether the seasonal gasoline transition effect observed in the U.S. market is also present in the regional markets of the Visegrad Group. Here, we redefine summer and winter periods in the following way: winter (October–May) and summer (June–September). The average Pb95 gasoline returns for the two redefined periods are displayed in Figure 3.

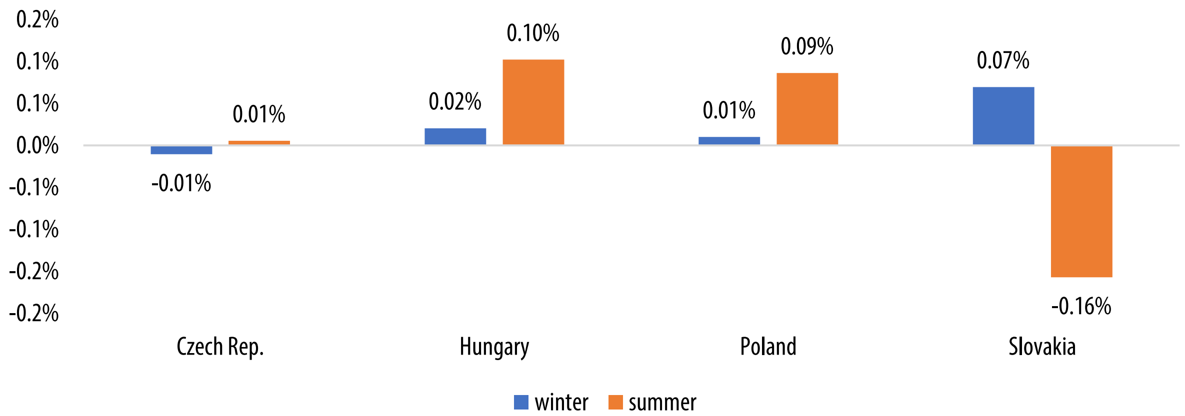


Figure 3. Average Pb95 gasoline returns for redefined periods (summer and winter) in the Czech Republic, Hungary, Poland and Slovakia from 2016 to 2020

Source: own elaboration based on data provided by e-petrol (n.d.).

Figure 3 shows positive average winter gasoline returns in V4 countries (except the Czech Republic) and positive average summer returns (except Slovakia).

For the redefined data, we perform the Shapiro–Wilk test. The results reported in Table 13 suggest rejection of the null hypothesis in all cases. Again, the Wilcoxon rank sum test is more appropriate for our data. Its results are given in Table 14. In all cases, we cannot reject the null hypothesis, so the redefined winter and summer gasoline returns do not differ significantly, suggesting there is no seasonal gasoline transition effect.

Table 13. The Shapiro–Wilk test for redefined periods (winter and summer)

Period	Czech Rep. Pb95	Hungary Pb95	Poland Pb95	Slovakia Pb95
Winter	0.961 326 (0.00)	0.943 611 (0.00)	0.869 141 (0.00)	0.697 203 (0.00)
Summer	0.900 743 (0.00)	0.895 995 (0.00)	0.961 056 (0.01)	0.743 417 (0.00)

Note: (•) – p-value
Source: own calculations based on data provided by e-petrol (n.d.).

Table 14. The seasonal transition effect – the Wilcoxon rank sum test

Fuel	Czech Rep. Pb95	Hungary Pb95	Poland Pb95	Slovakia Pb95
z	0.294 168 (0.77)	0.015 806 (0.99)	0.332 805 (0.74)	– 1.02 739 (0.30)

Note: (•) – p-value
Source: own calculations based on data provided by e-petrol (n.d.).

Next, we estimate simple regressions with a seasonal dummy, taking the value of 1 if month t falls in the June–September period and 0 otherwise. The results are reported in Table 15. They do not find a significant seasonal transition effect for the gasoline market in the Visegrad Group.

Table 15. The seasonal transition effect – simple regression

Period	Czech Rep. Pb95	Hungary Pb95	Poland Pb95	Slovakia Pb95
Summer	0.000 159 (0.96)	0.000 816 (0.71)	0.000 762 (0.65)	– 0.002 267 (0.36)

Note: (•) – p-value
Source: own calculations based on data provided by e-petrol (n.d.).

The study ends with the estimation of the GARCH (1, 1) models with the seasonal transition effect dummy and constant for the Hungarian, Polish and Slovakian gasoline markets (for the Czech Republic, the matrix was not positive definite). The results given in Table 16 do not reveal significant seasonal transition effects in the three examined gasoline markets, either.

Table 16. The seasonal transition effect – GARCH (1, 1) approach

Estimate	Hungary Pb95	Poland Pb95	Slovakia Pb95
Const.	0.00125 (0.33)	0.00073 (0.29)	0.00137 (0.32)
b_1	-0.00078 (0.71)	-0.00045 (0.72)	-0.00288 (0.22)
$\hat{\omega}$	0.00004 (0.02)	0.00002 (0.10)	0.00008 (0.01)
$\hat{\alpha}$	0.08390 (0.0290)	0.43829 (0.0013)	0.09184 (0.0239)
$\hat{\beta}$	0.76185 (0.00)	0.54965 (0.00)	0.67807 (0.00)

Note: (•) – p-value
Source: own calculations based on data provided by e-petrol (n.d.).

Conclusion

This paper examined seasonal patterns in the performance of regional fuel markets in the Visegrad Group. The data covered Pb95 gasoline and diesel fuel weekly prices from January 2016 through December 2020. The quantitative analysis was based on logarithmic returns, and it employed a range of statistical and econometric tools, such as the Wilcoxon rank sum test, simple regressions, and the GARCH models. The research focused on investigating two important calendar effects: the month-of-the-year effect and the Halloween effect, but it also considered the seasonal gasoline transition effect. Detecting some calendar anomalies, i.e., significant variations in gasoline and diesel returns that follow certain patterns or trends over time would be of great interest to consumers as they may shift purchases to save the cost (for many consumers, expenditures on fuels occupy some significant percentage of households' disposable income).

Even though it may not be a huge benefit for those individual consumers who have to refuel their cars regularly and pay whatever the price is, farmers would be able to save some money by purchasing diesel several months ahead. For business, in particular for fleet managers, recognizing market patterns may bring several advantages. For example, if a company supplies some vehicles with fuel, the best idea is to do it when the prices of fuel are the most favorable. This kind of information could also be used by oil processing companies to increase their profitability, as the existence of seasonality makes sales more predictable. Therefore, firms may try to trigger a rise in prices just before periods of expected high demand, resulting in significantly greater average returns.

However, the research presented in this paper does not bring clear evidence for significant seasonal patterns in the performance of regional fuel markets in the Visegrad Group, as the application of different methods provides mixed results. For example, when it comes to the analysis of the month-of-the-year effects, the Wilcoxon rank sum test shows that in Poland, the average January gasoline return differs significantly from April, August, and December's average returns and the average January diesel return is significantly different from the December return. Simple regressions detect a significant positive October effect for gasoline and a significant negative April effect for diesel in Slovakia. The GARCH (1, 1) models reveal several significant monthly effects: the March effect for gasoline and diesel in Poland, the April effect for gasoline in Poland, the May effect for gasoline and diesel in Hungary and Poland, the June effect for diesel in the Czech Republic, the August effect for diesel in Hungary and Poland, the October effect for gasoline in Poland and Slovakia, and diesel in Hungary, and the December effect for diesel in Poland. Thus, the results of the Wilcoxon rank sum test are consistent with the GARCH (1, 1) estimates in the case of a gasoline April effect and a diesel December effect in Poland. Meanwhile, simple regression and GARCH (1, 1) estimates are consistent for a gasoline October effect in Slovakia. None of the methods applied found a significant Halloween effect, a reverse Halloween effect or a gasoline seasonal transition effect on the regional fuel markets of the Visegrad Group.

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Analiza sezonowych prawidłowości na rynkach paliw Grupy Wyszehradzkiej

Celem pracy jest weryfikacja występowania sezonowych prawidłowości na rynkach paliw w krajach Grupy Wyszehradzkiej (V4), tj. w Czechach, na Węgrzech, w Polsce i na Słowacji. W odróżnieniu od wielu opracowań analizujących globalne rynki ropy ta praca koncentruje się na regionalnych detalicznych rynkach paliw. Dane empiryczne stanowią średnie tygodniowe ceny benzyny bezołowiowej Pb95 oraz oleju napędowego w okresie od stycznia 2016 do grudnia 2020 roku. Wykorzystane metody obejmują szereg narzędzi statystycznych i ekonometrycznych, takich jak test sumy rang Wilcoxona, regresja prosta oraz uogólnione modele autoregresyjne z warunkową heteroskedastycznością (GARCH). W badaniach skupiono się na analizie dwóch ważnych efektów kalendarzowych: efektu miesiąca w roku i efektu Halloween, ale uwzględniono również efekt sezonowej zmiany benzyny. Analiza empiryczna przedstawiona w pracy nie dostarczyła jednoznacznych dowodów na występowanie istotnych statystycznie prawidłowości na rynkach paliw w Grupie Wyszehradzkiej, gdyż wyniki uzyskane w konsekwencji zastosowania poszczególnych metod nie były jednoznaczne. Niemniej wnioski sformułowane na podstawie testu Wilcoxona są zgodne z wnioskami z modeli GARCH (1, 1) ujawniającymi efekt kwietnia dla benzyny i efekt grudnia dla oleju napędowego w Polsce. Ponadto wyniki regresji prostej i modelu GARCH (1, 1) wskazują efekt października dla benzyny na Słowacji. Natomiast żadna z zastosowanych metod nie pozwoliła wykryć efektu Halloween ani odwrotnego efektu Halloween czy też efektu sezonowej zmiany benzyny na rynkach paliw Grupy Wyszehradzkiej. Otrzymane wnioski dają nowy wgląd w rynki paliw Grupy Wyszehradzkiej i mogą być istotne dla podmiotów zajmujących się przetwórstwem ropy naftowej, przedsiębiorstw handlu detalicznego, firm transportowych i dystrybucyjnych, rolników czy konsumentów indywidualnych.

Słowa kluczowe: rynek paliw, sezonowe prawidłowości, Grupa Wyszehradzka, test Wilcoxona, regresja, model GARCH