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# VERIFICATION OF THE WEAK-FORM INFORMATIONAL EFFICIENCY OF FUEL MARKETS IN THE VISEGRAD GROUP

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**Abstract:** The paper aims at examining the weak-form informational efficiency of fuel markets in the Visegrad Group (V4) countries: the Czech Republic, Hungary, Poland and Slovakia from January 2016 through December 2020. For this purpose, the following statistical tests were applied: the runs test, the variance ratio test, the autocorrelation tests, the unit root tests. The tests provided mixed results not giving a definitive answer to the question of whether V4 fuel markets were informationally efficient in a weak form. The only exception is Slovakia where gasoline and diesel prices followed random walk, providing evidence in favor of the weak-form informational efficiency of the market.

**Keywords:** informational efficiency, fuel market, Visegrad Group

**JEL classification:** G14, C12, Q02

## INTRODUCTION

The concept of the market informational efficiency is a key element of the theory of efficient capital markets, as formulated and conceptually developed by Eugene Fama

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[Fama 1965, 1970, 1991, 1998][1]. According to the theory of informational efficiency, the prices of financial instruments at any time reflect all available information, both current (including historical) and rationally anticipated. Thus, forecasting financial assets prices for the next period is impossible because assumptions about the broadly understood future (in the sense of rational anticipation) are reflected in the current price [Starzeński 2011]. In other words, on an informationally efficient capital market the prices of financial instruments fully and quickly reflect all available information.

To make the empirical verification of informational efficiency possible, Fama [1970] proposed three hypotheses referring to three forms of informational efficiency:

– weak-form efficient market hypothesis, according to which the information set refers to historical prices only,
– semi-strong-form efficient market hypothesis, in which – additionally – publicly available information (e.g., coming from corporate balance sheets) is considered,
– strong-form efficient market hypothesis, where not only publicly but also privately available information (e.g., by investors having monopoly access to information relevant for price formation) is accounted for.

The rejection of the weak-form efficient market hypothesis implies the lack of semi-strong and strong efficiencies.

Since Fama's pioneering work, many studies have been conducted on the efficiency of financial markets, with the main focus dedicated to the stock market. However, in the 1980s, research on the informational efficiency of commodity markets, primarily the oil market, were initiated. In the last decade, this issue has been explored, for example, by Zahng et al. [2014], Górska, Krawiec [2016], Dimitriadou et al. [2018], Ghazani, Ebrahimi [2019], Bohl et al. [2021], Espinosa-Paredes et al. [2022] or Moyo et al. [2023], who mostly focused their research on the Brent and WTI oil markets. To our best knowledge relatively little work has been done on examining fuel domestic retail markets ([Hunter, Tabaghdehi 2013], [Valadkhani 2013], [Rosado et al. 2021]).

The aim of this paper is to verify the hypothesis of the weak-form informational efficiency of fuel markets in the Visegrad Group. The dataset consists of weekly average prices of basic fuels (gasoline Pb95 and diesel) in the Czech Republic, Hungary, Poland and Slovakia from January 2016 through December 2020. The following statistical tests verifying the randomness of the time series were used for the purpose of the analysis: runs test, variance ratio tests, autocorrelation tests, unit root tests. They are commonly used in examining the weak-form informational efficiency.

[1] The origins of the theory are admittedly disputed. Osińska [2006] states that the concept of the efficient market was first proposed by Bachelier back in 1900, and only after several dozen years reactivated by Fama, whose works are most frequently cited in the literature.

# METHODOLOGY

To verify the weak-form efficient market hypothesis, different statistical tests investigating the randomness of price changes may be applied. The popular tests that examine whether the time series is a random walk series include: unit root test, test for autocorrelation coefficients, test for variance ratios, and runs test [Witkowska et al. 2008].

**Runs test**

A run in the market is defined as a sequence of changes in quotations in the same direction (i.e. a series of increasing values, or a series of decreasing values) of any length. In this case, fractions are compared to the distribution that the data would follow if the investigated process was a random walk. If price changes are random, the probability of a further decline after a price decline should be equal to the probability of an increase. This would mean that a similar number of runs and sign changes should be expected in a large sample of observations.

When modeling the behavior of commodity prices, it is assumed that there are sequences of positive values, negative values and zeros. Then, in order to perform the runs test, an auxiliary variable $R_t^*$ is introduced, such that:

$$R_t^* = \begin{cases} 1, & \text{if} \quad R_t > 0 \\ 0, & \text{if} \quad R_t = 0 \\ -1, & \text{if} \quad R_t < 0 \end{cases}.$$

The null hypothesis $H_0$: "$R_t^*$ is a white noise" is tested against $H_1$: "$R_t^*$ is not a white noise".

To verify the hypothesis, $K$ statistic is used, which for large samples is approximately asymptotically normally distributed.

Statistic $K$ is given by:

$$K = \frac{H - E(\tilde{H})}{\sqrt{War(\tilde{H})}}, \tag{1}$$

where: $H$ is conditional realization of a random variable $\tilde{H}$ and denotes the total number of runs.

To perform the runs test, a distinction is made between continuous sequences of positive, zero and negative returns $R_t^*$. To this end, an auxiliary variable $h_t$ is introduced:

$$h_t = \begin{cases} 0, & \text{if } R_t^* = R_{t+1}^* \\ 1, & \text{if } R_t^* \neq R_{t+1}^* \end{cases}.$$

Accordingly, if $h_t = 1$, $R_{t+1}$ starts a new run.

Finally, the total number of runs is:

$$H = 1 + \sum_{t=1}^{n-1} h_t, \tag{2}$$

where $n$ is the length of a run.

If the investigated series consists of $n_1$ positive returns, $n_2$ with values of zero and $n_3$ negative returns, then the mean and variance of the random variable $\widetilde{H}$ are defined by the formulas [Taylor 1986]:

$$E(\widetilde{H}) = n + 1 - \frac{\sum_{j=1}^{3} n_j^2}{n}, \tag{3}$$

$$Var(\widetilde{H}) = \frac{\sum_{j=1}^{3} n_j^2\left(\sum_{j=1}^{3} n_j^2+n+n^2\right)-2n\sum_{j=1}^{3} n_j^3-n^2}{n^3-n}. \tag{4}$$

If $|K| > 1.96$, then the null hypothesis is rejected at the 0.05 level. When $K < 0$, there are trends in the data. $K > 0$ implies the mean reversion [Taylor 1986].

**Variance ratio tests**

When performing the variance ratio test, it is assumed that there are $nk + 1$ spot prices. The variance ratio test is used to verify whether the equation:

$$p_t = \mu + p_{t-1} + \varepsilon_t, \qquad t = 1, \ldots, nk \tag{5}$$

where $p_t$ is price at time t, $\mu$ is a constant term and $\varepsilon_t$ is the error term, is a proper model for the analyzed price series. Specifically, the null hypothesis of this test states that equation (5) is the right model for the series of prices of assets.

The model can be tested in two variants:

- $\varepsilon_t$ are independent and follow the same normal distribution with the expected value of zero and the same variance (assumption 1),
- $\varepsilon_t$ are uncorrelated and have a finite variance (assumption 2).

By verifying these two assumptions, it is possible to determine the reason for the potential rejection of the null hypothesis: Is it heteroscedasticity of $\varepsilon_t$ or rather autocorrelation?

Assuming that the assumption 1 is true and transforming the model (5), we have:

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) = \mu + \varepsilon_t. \tag{6}$$

This means that the continuously compound returns $r_t$ follow a normal distribution with expected value $\mu$ and variance $\varepsilon_t$. Also, assuming that individual returns are independent, the sample variance of $k$-period return is $k$ times the sample variance of one-period return. Thus, if $H_0$ is true, i.e. prices are generated by a stochastic process given by the formula (5) and $\varepsilon_t$ satisfies assumption 1, then:

$$\frac{var(r_k)}{k \cdot var(r_1)} = 1, \tag{7}$$

where $r_k$ is a logarithmic return from $k$ moments.

Therefore, the test of the null hypothesis can be based on the quotient of the variance, given by the left side of equation (7). If $H_0$ is true, the variance ratio calculated from the sample should be equal to unity.

The distribution of the test statistics (variance ratio):

$$z(k) = \frac{IW_k - 1}{\sqrt{L(k)}}, \tag{8}$$

where:

$IW(k) = \frac{\overline{var}(r_k)}{k \cdot \overline{var}(r_1)}$,

$\overline{var}(r_1) = \frac{1}{nk-} \sum_{t=1}^{nk} (p_t - p_{t-1} - \overline{p})^2$,

$\overline{var}(r_k) = \frac{1}{(nk-k-1)(1-1/n)} \sum_{t=k}^{nk} (p_t - p_{t-k} - k\overline{p})^2$,

$\bar{p} = \frac{1}{nk} \sum_{t=1}^{nk} (p_t - p_{t-1})$,

$L(k) = \frac{3nk^2}{2(2k-1)(k-1)}$,

follows standard normal distribution asymptotically [Lo, MacKinlay 1989].
Assuming that the assumption 2 is true, the null hypothesis can be verified using the statistic:

$$z^*(k) = \frac{IW_k - 1}{\sqrt{L^*(k)}}, \tag{9}$$

where:

$L^*(k) = \sum_{j=1}^{k-1} \left[ \left( \frac{2(k-j)}{k} \right)^2 \cdot V(j) \right]$,

$V(j) = \frac{\sum_{t=j+1}^{nk} (p_t - p_{t-1} - \overline{p})^2 \cdot (p_{t-j} - p_{t-j-1} - \overline{p})^2}{\left[ \sum_{t=1}^{nk} (p_t - p_{t-1} - \overline{p})^2 \right]^2}$.

It also follows standard normal distribution.

Statistics $z(k)$ and $z^*(k)$ allow the verification of the null hypothesis, answering the question of whether equation (5) may properly model the analyzed prices.

**Autocorrelation tests**

The autocorrelation test examines whether the data in the time series are correlated or not. The portmanteau test (Box-Pierce) and adjusted portmanteau test (Box-Ljung) examine whether the price changes are independent random variables with identical distributions.

Autocorrelation test verifies the following null hypothesis:

$H_0$: $\rho = 0$ (returns are not correlated with each other)

against

$H_1$: $\rho \neq 0$ (returns are correlated).

To verify the null hypothesis, the autocorrelation coefficient of returns given by the following formula may be used:

$$\hat{\rho}(k) = \frac{\sum_{t=1}^{T-k} (R_t - \bar{R}_T)(R_{t+k} - \bar{R}_T)}{\sum_{t=1}^{T} (R_t - \bar{R}_T)^2}, \tag{10}$$

where:

$\hat{\rho}(k)$ is the autocorrelation of order $k$,

$\bar{R}_T$ is the mean return ($\bar{R}_T = \frac{1}{T} \sum_{t=1}^{T} R_t$),

$T$ is the number of observations,

$R_t$ is the rate of return at time $t$,

$R_{t+k}$ is the rate of return of prices that are $k$ moments distant from each other. Assuming the truth of the null hypothesis $H_0$, the statistic

$$S = \sqrt{T}\hat{\rho}(k) \tag{11}$$

follows standard normal distribution [Taylor 1986]. The null hypothesis is rejected at 0.05 level, when the absolute value of the statistic $S$ is greater than 1.96.

The aim of the Box-Pierce and Box-Ljung tests is to verify the following null hypothesis:

$H_0$: $\rho_1 = \rho_2 = \ldots = \rho_m = 0$ (rates of return are uncorrelated)

against

$H_1$: $\rho_i \neq 0$, i={1, …, m} (rates of return are correlated).

These tests examine the significance of the subsequent correlation coefficients.

In the case of the Box-Pierce test, the statistic is:

$$Q_m = T\sum_{k=1}^{m}\hat{\rho}(k)^2, \tag{12}$$

and in the Box–Ljung test, it is:

$$Q'_m = T(T+2)\sum_{k=1}^{m}\frac{\hat{\rho}(k)^2}{T-k}, \tag{13}$$

where:

$\hat{\rho}(k)$ – autocorrelation coefficient of order $k$, for $k$ = 1,…, $m$ as in equation 10,

$T$ – the length of the time series,

$m \approx ln(T)$ – maximum delay.

Statistics $Q$ ($Q'$) consist of numerous autocorrelation coefficients, and follow the $\chi^2_m$ (chi-squared) distribution with $m$ degrees of freedom [Mills 1999]. When the value of empirical statistic $Q$ exceeds the value of $\chi^2_m$ representing the theoretical distribution, $H_0$ can be rejected at the pre-specified significance level. According to equations (12) and (13), the number of degrees of freedom $m$ is the number of autocorrelation coefficients, which are taken into account when calculating statistics $Q$ or $Q'$.

**Unit root tests**

Unit root tests may be applied to verify whether the time series follow random walk, which means they are nonstationary[2].

A time series is stationary if its mean and variance do not vary systematically over time and the covariance between two time periods depends only on the distance (or gap or lag) between the two time periods and not on the actual time at which the covariance is computed. Such a series is also referred to as the series that is integrated of order zero or as *I*(0). Most economic time series are nonstationary. However, it is possible to convert them to a stationary series by taking the first differences. Thus, a nonstationary series is integrated of order *d*, denoted *I*(*d*) if it becomes stationary after being first differenced *d* times [Greene 2018].

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[2] According to Gujarati [2003], the terms nonstationarity, random walk, and unit root can be treated as synonymous.

There are several tests of stationarity. One of the most popular is the augmented Dickey-Fuller test (ADF). It is carried out in the context of the model:

$$y_t = \boldsymbol{\beta}'\boldsymbol{D}_t + \phi y_{t-1} + \sum_{j=1}^{p} \psi_j \Delta y_{t-j} + \varepsilon_t, \tag{14}$$

where $y_t$ represents the time series of the phenomenon under investigation, $\phi$ and $\psi_j$ are the estimated coefficients on the lagged values of $y$, $\boldsymbol{D}_t$ is a vector of deterministic terms (constant, trend, etc) and $\boldsymbol{\beta}'$ is a vector of the corresponding estimated coefficients. The number of lagged difference terms to include is often determined empirically[3], the idea being to include enough terms so that the error term in (14) is serially uncorrelated. The error term $\varepsilon_t$ is also assumed to be homoscedastic.

Under the null hypothesis that $y_t$ is $I(1)$, which implies $\phi = 1$, there are two approaches to carrying out the test. The conventional $t$ ratio:

$$ADF_t = \frac{\hat{\phi} - 1}{SE(\phi)} \tag{15}$$

with the revised set of critical values that may be used for a one-sided test.
The second approach is based on the statistic:

$$ADF_n = \frac{t(\hat{\phi} - 1)}{1 - \hat{\psi}_1 - \cdots - \hat{\psi}_p} \tag{16}$$

Dickey and Fuller [1979] computed the critical values based on Monte Carlo simulations and later MacKinnon [1991] presented more extensive tables [Gujarati 2003].
An alternative formulation in first differences may prove convenient:

$$\Delta y_t = \boldsymbol{\beta}'\boldsymbol{D}_t + \pi y_{t-1} + \sum_{j=1}^{p} \psi_j \Delta y_{t-j} + \varepsilon_t, \tag{17}$$

where:
$\pi = \phi - 1$.
The unit root test is carried out as before by testing the null hypothesis $\pi = 0$ against $\pi < 0$ and the $t$ test, $ADF_t$, may be used [Greene 2018].

Kwiatkowski et al. [1992] devised an alternative to the Dickey-Fuller test. They start with the model:

$$y_t = \boldsymbol{\beta}'\boldsymbol{D}_t + \mu_t + u_t \tag{18}$$
$$\mu_t = \mu_{t-1} + \varepsilon_t,\ \varepsilon_t \backsim WN(0, \sigma_\varepsilon^2),$$

where $\boldsymbol{D}_t$ contains deterministic components, $u_t$ is $I(0)$ and may be heteroscedastic. Notice that $\mu_t$ is a pure random walk with innovation variance $\sigma_\varepsilon^2$. The null hypothesis that $y_t$ is $I(0)$ is formulated as $H_0$: $\sigma_\varepsilon^2 = 0$, which implies that $\mu_t$ is constant. The KPSS statistic is the Lagrange multiplier (LM) or score statistic for testing $\sigma_\varepsilon^2 = 0$ against the alternative that $\sigma_\varepsilon^2 > 0$ and is given by:

$$KPSS = \frac{\sum_{t=1}^{T} \hat{S}_t^2}{T^2 \hat{\lambda}^2}, \tag{19}$$

[3] On the basis of large number of simulations, Schwert [1989] found that $p_{\max}$ set as the integer part of $[12 \times (T/100)^{0.25}]$ gave good results.

where $\hat{S}_t = \sum_{j=1}^{t} \hat{u}_j$, $\hat{u}_t$ is the residual of a regression of $y_t$ on $\boldsymbol{D}_t$ and $\hat{\lambda}^2$ is a consistent estimate of the long-run variance of $u_t$ using $\hat{u}_t$ [Zivot, Wang 2006].

It has been argued that tests with stationarity as null can be used to confirm the results of the usual unit root tests. If both tests reject their nulls, then we have no confirmation of stationarity. However, if test 1 rejects the null, but test 2 does not (or vice versa) we obtain confirmation [Maddala 2005].

## EMPIRICAL DATA AND RESULTS

The dataset used for the purpose of the research covers weekly prices (260 observations) of basic fuels: gasoline Pb95 and diesel in the Czech Republic, Hungary, Poland and Slovakia from January 2016 through December 2020. The prices are expressed in domestic currencies per 1 liter. The data is provided by e-petrol.pl (www.e-petrol.pl). The quantitative analysis is based on logarithmic prices (log-prices) and their first differences – logarithmic returns (log-returns).

### Runs test

Table 1 presents the values of *K* statistic (equation (1)), calculated for each country for gasoline and diesel logarithmic returns. The results show that we cannot reject the null hypothesis at 0.05 in the case of the Czech Republic and Slovakia for both fuels. Thus, we can expect $R_t^*$ to be generated by the white noise ($|K| < 1.96$). In consequence, both fuels markets in the Czech Republic and Slovakia are found to be informationally efficient in a weak-form. Additionally, negative values of *K* suggest the existence of trends in fuels returns.

Table 1. Values of *K* statistic

| Country | Fuel | |
|---|---|---|
| | Gasoline | Diesel |
| Czech Republic | -0.71 | 1.70 |
| Hungary | -2.89* | -4.97* |
| Poland | -5.45* | -5.79* |
| Slovakia | -1.43 | -0.34 |

Source: own calculations Note: *$H_0$ rejection at the 0.05 level

### Variance ratio test

Results of variance ratio test are reported in Table 2 (the tests were performed for logarithmic returns from 1 up to 10 weeks ($k = 1, \ldots, 10$)). All *z(k)* statistics given in Table 2 are not significant at 0.05. Thus, the null hypothesis cannot be rejected and fuel prices are likely to be generated by the stochastic process fulfilling assumption 1. Moreover, model (5), fulfilling assumption 2, is not a good approximation of analyzed fuels prices (in the case of gasoline in the Czech Republic, Hungary and Poland (for $k > 2$), in the case of diesel in the Czech Republic and Poland).

Table 2. Results of the variance ratio test

| Fuel | Country | k | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Gasoline | Czech Rep. | IW(k) | 0.78 | 0.59 | 0.51 | 0.51 | 0.51 | 0.52 | 0.53 | 0.51 | 0.51 |
| | | z(k) | 0.00 | 0.00 | -0.01 | -0.01 | -0.01 | -0.01 | -0.02 | -0.02 | -0.02 |
| | | z*(k) | -2.90* | -3.56* | -3.43* | -2.95* | -2.63* | -2.37* | -2.18* | -2.09* | -2.37* |
| | Hungary | IW(k) | 1.11 | 1.27 | 1.40 | 1.50 | 1.58 | 1.64 | 1.71 | 1.75 | 1.81 |
| | | z(k) | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.03 | 0.03 |
| | | z*(k) | 1.50 | 2.52* | 3.05* | 3.28* | 3.32* | 3.32* | 3.33* | 3.29* | 3.87* |
| | Poland | IW(k) | 1.18 | 1.41 | 1.61 | 1.76 | 1.87 | 1.99 | 2.10 | 2.18 | 2.26 |
| | | z(k) | 0.00 | 0.00 | 0.01 | 0.01 | 0.02 | 0.03 | 0.04 | 0.04 | 0.05 |
| | | z*(k) | 1.19 | 2.01* | 2.55* | 2.87* | 3.07* | 3.30* | 3.48* | 3.59* | 6.07* |
| | Slovakia | IW(k) | 1.05 | 1.05 | 1.06 | 1.08 | 1.11 | 1.12 | 1.13 | 1.13 | 1.12 |
| | | z(k) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |
| | | z*(k) | 0.64 | 0.40 | 0.42 | 0.45 | 0.53 | 0.55 | 0.54 | 0.50 | 0.53 |
| Diesel | Czech Rep. | IW(k) | 0.52 | 0.47 | 0.42 | 0.39 | 0.36 | 0.35 | 0.33 | 0.32 | 0.31 |
| | | z(k) | 0.00 | -0.01 | -0.01 | -0.01 | -0.02 | -0.02 | -0.02 | -0.02 | -0.03 |
| | | z*(k) | -3.87* | -3.09* | -2.89* | -2.70* | -2.65* | -2.53* | -2.49* | -2.41* | -3.72* |
| | Hungary | IW(k) | 1.00 | 1.00 | 0.98 | 0.98 | 0.98 | 0.98 | 0.98 | 0.99 | 1.00 |
| | | z(k) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | z*(k) | 0.04 | -0.02 | -0.12 | -0.11 | -0.08 | -0.09 | -0.09 | -0.06 | -0.01 |
| | Poland | IW(k) | 1.44 | 1.83 | 2.09 | 2.28 | 2.43 | 2.56 | 2.66 | 2.74 | 2.82 |
| | | z(k) | 0.00 | 0.01 | 0.02 | 0.02 | 0.03 | 0.04 | 0.05 | 0.06 | 0.07 |
| | | z*(k) | 4.01* | 5.23* | 5.68* | 5.95* | 6.11* | 6.24* | 6.30* | 6.29* | 8.63* |
| | Slovakia | IW(k) | 1.01 | 1.05 | 1.04 | 1.07 | 1.11 | 1.14 | 1.15 | 1.18 | 1.19 |
| | | z(k) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 |
| | | z*(k) | 0.21 | 0.65 | 0.36 | 0.54 | 0.70 | 0.85 | 0.82 | 0.90 | 1.08 |

Source: own calculations Note: *$H_0$ rejection at the 0.05 level

## Autocorrelation tests

Table 3 presents results of the autocorrelation test for logarithmic returns, where autocorrelations of order $k = 1, 2, \ldots, 10$ are verified.

Table 3. Values of autocorrelation of order *k* (rho) and *S* statistics

| | | Gasoline | | | | Diesel | | | |
|---|---|---|---|---|---|---|---|---|---|
| *k* | | Czech Rep. | Hungary | Poland | Slovakia | Czech Rep. | Hungary | Poland | Slovakia |
| 1 | rho(1) | -0.22 | 0.09 | 0.16 | 0.03 | -0.22 | -0.01 | 0.42 | 0.00 |
| | *S* | -3.57* | 1.44 | 2.64* | 0.54 | -3.57* | -0.18 | 6.83* | -0.05 |
| 2 | rho(2) | -0.18 | 0.18 | 0.26 | -0.03 | -0.18 | -0.01 | 0.37 | 0.05 |
| | *S* | -2.86* | 2.86* | 4.14* | -0.49 | -2.86* | -0.16 | 5.92* | 0.82 |
| 3 | rho(3) | 0.02 | 0.10 | 0.15 | 0.03 | 0.02 | -0.02 | 0.14 | -0.07 |
| | *S* | 0.39 | 1.62 | 2.35* | 0.48 | 0.39 | -0.27 | 2.24* | -1.17 |
| 4 | rho(4) | 0.14 | 0.04 | 0.06 | 0.01 | 0.14 | 0.03 | 0.12 | 0.09 |
| | *S* | 2.17* | 0.66 | 0.91 | 0.20 | 2.17* | 0.41 | 1.95 | 1.45 |
| 5 | rho(5) | -0.01 | 0.01 | 0.04 | 0.03 | -0.01 | 0.00 | 0.04 | 0.04 |
| | *S* | -0.10 | 0.13 | 0.68 | 0.50 | -0.10 | 0.04 | 0.64 | 0.67 |
| 6 | rho(6) | 0.02 | 0.05 | 0.12 | -0.03 | 0.02 | -0.02 | 0.06 | 0.02 |
| | *S* | 0.29 | 0.85 | 1.89 | -0.45 | 0.29 | -0.37 | 0.94 | 0.30 |

| | | Gasoline | | | | Diesel | | | |
|---|---|---|---|---|---|---|---|---|---|
| $k$ | | Czech Rep. | Hungary | Poland | Slovakia | Czech Rep. | Hungary | Poland | Slovakia |
| 7 | rho(7) | 0.00 | 0.04 | 0.06 | -0.01 | 0.00 | 0.00 | 0.01 | -0.09 |
| | $S$ | -0.05 | 0.59 | 0.95 | -0.17 | -0.05 | 0.07 | 0.16 | -1.37 |
| 8 | rho(8) | -0.07 | -0.02 | -0.02 | -0.04 | -0.07 | 0.02 | -0.04 | 0.08 |
| | $S$ | -1.11 | -0.39 | -0.25 | -0.64 | -1.11 | 0.38 | -0.61 | 1.29 |
| 9 | rho(9) | 0.04 | 0.04 | 0.01 | -0.03 | 0.04 | 0.03 | -0.02 | -0.04 |
| | $S$ | 0.71 | 0.71 | 0.20 | -0.48 | 0.71 | 0.40 | -0.38 | -0.58 |
| 10 | rho(10) | -0.06 | -0.08 | -0.09 | -0.05 | -0.06 | 0.01 | -0.05 | -0.06 |
| | $S$ | -0.91 | -1.31 | -1.39 | -0.74 | -0.91 | 0.12 | -0.84 | -0.92 |

Source: own calculations Note: *$H_0$ rejection at the 0.05 level

Results in Table 3 suggest rejection of the null hypothesis $H_0$: „fuel prices are independent random variables" for both gasoline and diesel in the Czech Republic and in Poland in the case of autocorrelation of orders $k = 1$ and $k = 2$, and also (only in Poland) when $k = 3$ and in the Czech Republic when $k = 4$ ($S > 1.96$). On the contrary, we cannot reject the null hypothesis for both of them in the case of autocorrelation of order $k = \{5, 6, 7, 8, 9, 10\}$. Although in most cases the null hypothesis cannot be rejected, values of coefficient of correlation $\hat{\rho}(k)$ differ from zero. However, their absolute values are small. Thus, we expect fuels prices to be autocorrelated, but the autocorrelations are too weak to let us draw definite conclusions.

**Box-Pierce and Box-Ljung tests**

Results of Box-Pierce and Box-Ljung tests, performed on logarithmic returns, are shown in Table 4. Different numbers of lags ($m$): 10, 20 and 30 were considered. Empirical values of $Q_m$ and $Q'_m$ statistics are compared to the theoretical values of chi-squared distribution: 18.31, 31.41 and 43.77, respectively.

Table 4. Values of Q and Q' statistics

| | | Fuel | | | | | |
|---|---|---|---|---|---|---|---|
| | | Gasoline | | | Diesel | | |
| Country | m | 10 | 20 | 30 | 10 | 20 | 30 |
| Czech Rep. | $Q_m$ | 28.43* | 37.78* | 44.73* | 68.96* | 92.36* | 100.11* |
| | $Q'_m$ | 28.93* | 38.96* | 46.74* | 69.93* | 94.96* | 103.69* |
| Hungary | $Q_m$ | 16.76 | 43.20* | 49.36* | 0.77 | 11.55 | 15.74 |
| | $Q'_m$ | 17.12 | 45.30* | 52.23* | 0.79 | 12.34 | 17.02 |
| Poland | $Q_m$ | 37.44* | 61.18* | 69.85* | 93.00* | 118.56* | 134.54* |
| | $Q'_m$ | 38.17* | 63.51* | 73.51* | 94.37* | 121.90* | 139.99* |
| Slovakia | $Q_m$ | 2.46 | 8.98 | 14.84 | 9.45 | 18.50 | 28.60 |
| | $Q'_m$ | 2.54 | 9.53 | 16.08 | 9.74 | 19.46 | 30.63 |

Source: own calculations Note: *$H_0$ rejection at the 0.05 level

Results in Table 4 suggest rejection of the null hypothesis regardless the number of lags in case of gasoline and diesel in the Czech Republic and Poland. All values of $Q_m$ and $Q'_m$ statistics are greater than respective theoretical values of chi-squared distribution. This lets us state that returns are correlated. Again, the correlations are too weak to draw definite conclusions. In the case of Slovakia, for both fuels, $H_0$ cannot be rejected as well as for diesel in Hungary.

**Unit root tests**

The last step of the research aims at examining the stationarity of the time series under consideration. Results of the ADF and KPSS tests performed on logarithms of prices (log-prices) and their first differences (log-returns) are reported in Table 5. The lag length is set to 15.

Table 5. Unit root tests results

| Fuel | Country | ADF | | KPSS | |
|---|---|---|---|---|---|
| | | log-prices | log-returns | log-prices | log-returns |
| Gasoline | Czech Rep. | -2.26 | -12.10* | 0.27* | 0.04 |
| | Hungary | -3.31 | -7.18* | 0.21* | 0.03 |
| | Poland5 | -3.00 | -7.95* | 0.28* | 0.04 |
| | Slovakia | -1.99 | -15.44* | 0.27* | 0.04 |
| Diesel | Czech Rep. | -2.19 | -27.24* | 0.32* | 0.06 |
| | Hungary | -2.25 | -16.18* | 0.30* | 0.04 |
| | Poland | -2.37 | -7.00* | 0.30* | 0.05 |
| | Slovakia | -1.15 | -16.18* | 0.31* | 0.05 |

Source: own calculations Note: *$H_0$ rejection at the 0.05 level

Results presented in Table 5 show that in the case of logarithmic prices, we are unable to reject the null hypothesis of presence of a unit root at the 0.05 level of the significance. For first differences (log-returns), we reject the null hypothesis. Hence, the results of the ADF test reveal that all series are $I(1)$ in nature. It means that log-prices of Pb95 gasoline and diesel are nonstationary, but their first differences are stationary. Results of the KPSS test confirm the findings based on the ADF test, so the original series (log-prices) are integrated of order 1. We may conclude they follow a random walk as a series that follows a random walk is clearly $I(1)$ (see [Ramanathan 2002]).

## CONCLUDING REMARKS

Fuels are major products whose prices influence prices of numerous goods and services.That is why investigating mechanisms determining fuel prices and their behavior is of great importance. This study is a contiuation of a former research that was aimed at detecting seasonal patterns (calendar effects) in the performance of fuel markets in the Visegrad Group [Krawiec, Górska 2024]. These results did not reveal the significant calendar effects, such as the Halloween effect, reverse Halloween efect or gasoline seasonal transition effect, which would be suggestive of the informational efficiency of these markets.

The focus of this paper was to explore the weak-form informational efficiency of fuel markets in the Visegrad Group (V4) countries (the Czech Republic, Hungary, Poland and Slovakia) from January 2016 through December 2020 using several statistical tests: the runs test, the variance ratio test, the autocorrelation tests, the unit root tests. The results obtained, however, do not provide a clear answer to the question of whether V4 fuel markets were informationally efficient in a weak-form. An exception here is Slovakia, where prices of gasoline and diesel followed random walk. This provides evidence in favor of the weak-form informational efficiency. The tests provided mixed results for the other investigated fuel markets.

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