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*The Causal Relationship Between Stocks, Gold, Crude Oil,  
and Bond Returns in Poland*

**Keywords:** gold; stocks; crude oil; bonds; VAR; Granger causality

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**Abstract**

**Theoretical background:** Capital investments involve taking risks to achieve a favourable rate of return. Investors are offered various options, including stocks, bonds, and commodities. The aforementioned investment opportunities are considered alternatives due to their varying price volatility and risk levels. Bonds and gold demonstrate a low or negative correlation with equities. On the other hand, crude oil and gold are positively correlated. An essential issue in analysing financial markets is to capture the dynamic behaviour of the financial time-series data, i.e. variables such as prices and returns on investments in assets mentioned above. In decision-making, investors should consider the causal relationship between asset classes, as some variables may contain important information about the future dynamics of other variables. The ability to predict future outcomes is crucial to reduce uncertainty. Vector autoregression (VAR) models are regarded as a useful modelling tool in investigating interrelations between financial instrument prices and returns.

**Purpose of the article:** The paper aims to evaluate the linkages between stock, gold, crude oil, and bond returns in Poland. We focus on analysing both the long-term equilibrium between logarithmic financial asset prices and the Granger causality between logarithmic returns in the short term.

**Research methods:** The causal relationships between the stocks, gold, crude oil, and bond logarithmic returns are investigated based on the VAR/VECM estimates. The empirical data cover the period from

December 2006 to January 2023. We use the following market data to measure the interrelations between the considered assets: WIG Index, gold and crude oil spot prices, and bond index reflecting the price movements on the Polish financial market. We carry out the test for stationarity employing the ADF and Phillips–Perron tests. The pre-estimation process also involves identifying the number of lags and conducting the Johansen cointegration test since variables are integrated of order one to examine the existence of the long-term equilibrium between the logarithmic prices of assets mentioned above. We use the Wald test for the models' parameters to indicate the type of Granger causality between logarithmic returns. The forecast error variance decomposition (FEVD) and impulse response functions (IRF) analysis is also applied. Moreover, the post-estimation procedure includes a test for parameters stability and white noise of residuals. All calculations are performed using Stata's standard software package.

**Main findings:** The results suggest that the markets we examined in Poland are cointegrated, meaning a long-term relationship exists between the prices of financial assets. Additionally, we prove that gold logarithmic prices have a negative impact on the stock index, indicating an inverse relationship between their price developments. We also discover that crude oil and bonds' effects on the stock market are positive. Although all  $\beta$  coefficients of the error correction equation are statistically significant, the short-term adjustment to equilibrium did not occur based on the  $\alpha$  coefficients of the short-term equations. According to the Granger causality analysis related to the VAR in first differences, gold price changes have a short-term impact on stock returns. In contrast, stock returns cause crude oil returns. However, we find no causal linkages in the remaining cases, suggesting that the variables are independent. Changes in asset prices are mainly attributed to their shocks, while observed impacts described by IFR function patterns die out quite quickly. Overall, results confirm that investors can combine gold and stocks in their portfolios, as these interrelated assets have alternative investment properties. Additionally, it is worth noting that the correlation between stock returns and crude oil or bonds is undesirable when constructing portfolios.

## Introduction

Investors are offered a variety of options for investing capital. The main asset classes to consider are stocks, bonds, and commodities (crude oil, precious metals). Compared to bonds, stocks are perceived as riskier since their prices are more volatile. Bonds constituting debt securities, especially treasury ones, are relatively safe investments and offer a stable income. Stock market investments are mainly viewed as alternatives to gold investments. Investors usually lose interest in gold when share prices rise and switch to precious metals if the share prices decline. Bonds and gold usually demonstrate a low or negative correlation with equities. Gold, which generates no interest, becomes a desirable investment alternative to bonds in periods of relatively low, and in particular negative, real interest rates. On the other hand, crude oil and gold are positively correlated. Crude oil prices have an impact on stock and gold prices. Increasing crude oil prices raises economic production costs and lowers stock prices (Singh, 2014; Beckmann et al., 2015; Tursoy & Faisal, 2018; Mamcarz, 2018). Investors' decisions to allocate capital to these markets determine the type and direction of causation between financial assets. Thus, these assets can be an investment alternative when the financial market faces turbulence. The following research hypothesis was formulated: rates of return on gold, crude oil, and bonds market constitute a Granger cause of the rates of returns on the Polish stock market.

This paper aims to evaluate the linkages between stock, gold, crude oil, and bond returns in Poland from both short- and long-term perspectives using the VAR/VECM approach. The Granger causality test is conducted to investigate the nature of the short-term interrelations. Additionally, the forecast-error variance decomposition (FEVDs) analysis is applied to measure the impact of each orthogonalised shock on the total forecast-error variance followed by an examination of the impulse response functions (IRFs) patterns.

To track the price fluctuations in the market that have been mentioned earlier, we utilise specific benchmarks such as the Warsaw Stock Exchange WIG Index (WIG), gold spot prices (GOLD\_PLN), Cushing, OK WTI Spot Price FOB (WTI\_PLN), all of which are expressed in Polish currency (PLN), and Treasury BondSpot Poland Index (TBSP.Index). The reasoning for choosing American WTI crude oil, retrieved from shales and oil sands instead of Brent crude oil is the recent growing popularity of the former type of crude oil, resulting in increased sales by North American exporters. On the other hand, long-term forecasts indicate that Brent crude oil may experience supply constraints due to the depletion of oil deposits in the North Sea.

To our knowledge, the Polish financial market has received less attention regarding the causal links between the considered set of assets. A mainly global approach was adopted, and the perspective of the leading financial markets was presented. Researchers focus on the countries classified as the key producers and consumers of gold and crude oil, the widely recognised stock and bond markets. Therefore, it is essential to investigate the causal links between assets considered from a local perspective, as both domestic and foreign investors may be interested in gaining knowledge about the interconnections between the main asset classes and be able to predict price changes in the Polish financial market which FTSE Russell currently classifies as a developed one.

## Literature review

Vector autoregression (VAR) models are helpful modelling tools in finance and economic analysis. The areas of interest are asset pricing, international finance, and market microstructure. They are applied to study financial market efficiency, stock return predictability, exchange rate dynamics, and information content of stock trades and market quality. Utilising VAR models, the interactions among economic and financial variables are investigated, and the dynamic behaviour of the financial time-series data can be captured. Another application is forecasting and Granger causality testing to indicate if some variables contain essential information about the future dynamics of other variables in the model. The relationships between variables in a VAR model can be studied using impulse response functions (IRF), which represent the responses of the model variables to shocks (impulses) affecting the system. Moreover, the influence of a one-unit shock on the system is measured by

variance decomposition reflecting the share of a given impulse to the variance of the forecast error (FEVD) in predicting the future value of each variable in the system. To capture not only the short-term but also the long-term impacts between variables, the VAR model can be transformed into a vector error correction model (VECM) if the long-term equilibrium (cointegration) between non-stationary variables exists (Wu & Zhou, 2015; Kusideł, 2000, pp. 48–50).

VAR/VECM models are widely used for analysing the dependencies between financial market instruments in economic research. Stocks, gold, bonds, and crude oil are the most commonly studied assets. Moreover, researchers tend to explore the impact of the exchange rates between different domestic currencies of analysed financial markets. The relationship between stock and gold was examined, *inter alia*, by Al-Ameer et al. (2018), who took the Frankfurt Stock Exchange index HDAX as a benchmark for equities. They confirm the existence of a long-term relationship between August 2004 and September 2016. However, no Granger causality was identified during the whole period or for three sub-periods, i.e. before, during, and after the financial crisis. The study devoted to the selected Central and East European countries, including Poland, Hungary, and the Czech Republic, is presented by Mamcarz (2021). The results indicate, apart from two instances of unilateral causality running from gold to stock returns, no causal relationships in any direction (independence) for the entire sample covering the period between December 1996 and December 2020. In the case of Hungary and the Czech Republic (significant at  $\alpha = 5\%$ ), the rates of return on the gold market determine the rates of return on the stock markets in these countries. After dividing the sample into two sub-periods, the first one before the 2007 financial crisis and the second one, examining this crisis and the beginning of the ongoing COVID-19 pandemic, no causal relationships are found between the analysed markets in the first sub-period. On the other hand, in the second sub-period, the rates of return on gold are the Granger cause to the rates of return on stocks in two countries, namely Poland and Hungary. Also, Tiwari et al. (2019) analysed correlations between gold markets and stock markets concerning Brazil, China, India, Indonesia, Korea, Mexico, Russia, and Turkey in a period from January 2002 to July 2018. They apply quantile-on-quantile regression (QQR) to investigate the Granger causality. Regarding the entire period, a weak positive correlation in quantile for gold and stock returns was present in the whole period and for two sub-periods (before and after the crisis), except for Turkey, China and Indonesia. The causality test-in-mean and causality test-in-variance confirm the causality from gold to stocks in some markets only after the crisis.

Another pair of financial assets under investigation are stocks and bonds. For instance, Zakamulin and Hunnes (2021) considered the structural breaks while analysing the long-term equilibrium and causality between stock-bond returns on the US market within one hundred and fifty years. Based on the VECM approach, they state that the long-term relationship existed between analysed assets in two sub-periods, i.e. 1871–1932 and 1958–2017. Also, short-term bond returns have an impact on

stock returns. The most recent period is in the interest of Deng et al. (2022), who analysed the Chinese stock and bond market between 2005–2021, including a full sample and three sub-samples: before, during, and after the financial crisis. They apply the VAR model to conduct the linear no-causality test proposed by Granger. Moreover, using the multi-quantile VaR Granger causality test and network topology, they aim to detect asymmetric risk spillovers among markets. Mutual linkages occur during the financial crisis, characterised by extreme market conditions. Based on their research, defensive stock industries tend to be favoured when facing upside risks, whereas offensive stocks are recommended to cope with the downside risks and limit losses. Additionally, government bonds have superior risk-hedging qualities and greater transparency than financial and corporate bonds. The research also deals with the relationship between the third possible pair of assets, i.e. stocks and crude oil. For instance, Enwereuzoh et al. (2021) focus on oil price shocks and stock returns in African countries defined as oil-exporting (Nigeria, Tunisia, and Egypt) and oil-importing (Botswana, South Africa, Kenya, and Mauritius) ones. They apply SVAR and a two-state regime smooth transition regression model to analyse the period from January 2000 to July 2018. The results confirm that, contrary to oil-importing countries, global demand shocks primarily affect stock returns for oil exporters. On the other hand, the oil supply shock does not impact the real stock return regardless of country type, while the oil-specific shock is significant in most countries. Moreover, the effects of the price shocks are asymmetric, with a more substantial influence in the case of negative changes.

The other combination of assets mentioned above is considered in research by Mensi et al. (2021). They apply the Markov-switching vector autoregressive model while examining the price-switching spillovers between the US and Chinese stocks, crude oil, and gold futures markets before and during the COVID-19 pandemic. The first regime lasted from January 2019 to February 2020, and the second covered the period between March and May 2020. Findings show that the changes in stock prices are mainly driven by their shocks. For the low-volatility regime, gold and oil price returns impact the Chinese stock market. Gold returns cause S&P 500 returns, while stock returns positively affect oil returns. In contrast, the inverse impacts for the high-volatility regime are identified. Gold also proved to be a solid safe haven while facing investment risks associated with the global health crisis.

The issue of dynamic spillovers and linkages between gold, crude oil, S&P 500, and other economic and financial variables in the US market is also analysed by Golitsis et al. (2022). They employ a vector autoregression (VAR) and the spillover index proposed by Diebold and Yilmaz (2012; 2014). The method also involves calculating generalised impulse response functions and generalised forecast error variance decompositions to explain the impact of shocks on the other variables. Referring to key findings, gold appears to be a strong hedge against the dollar exchange rate, while inflation drivers are crude oil and Treasury bills. Moreover, a strong spillover effect exists between the exchange rate and gold returns. They show that the net

spillovers (positive vs negative) and, in effect, the recipient/transmitter position of the included markets changes during extreme market events. Economic policy uncertainty, stock market returns, and crude oil returns are the primary transmitters, while the opposite role is attributed to Treasury bills and CPI. On the other hand, gold and exchange rates are receivers and transmitters over the sample period from January 1986 to December 31, 2019.

The causal linkages between the stock market in Poland, represented by WIG20, and the currency market, including the USD/PLN and the EUR/PLN exchange rates, are examined by Sekuła (2018) from April 2000 to December 2017. A two-dimensional model of vector autoregression is applied to capture the interdependences. The author reports that changes in USD/PLN and EUR/PLN are the reason for WIG20 changes. Moreover, WIG20 changes are also the Granger cause for changes in the EUR/PLN exchange rate, confirming the bidirectional causality between the stock index and the latter exchange rate under consideration in this study. The analysis is also conducted in sub-periods: pre-accession to the EU, after accession to the EU, the financial crisis in 2007–2009, and the post-crisis time horizon. The feedback relationship is not confirmed then.

The method based on standard VAR and Markov-switching VAR models is also applied by Chkili (2022), who analysed the relationship between gold, oil, and Islamic stock markets. The data covers the period between 1996–2020, including the recent COVID-19 pandemic crisis. According to VAR estimates, the relationship between oil and Islamic stock markets is positive, which means the crude oil market is being financialised. On the other hand, the relationship between the Islamic equity market and gold is negative. The results concerning the Markov-switching model indicate the hedging properties of gold against the stock price changes for the low-volatility regime and its safe haven role for the high-volatility one.

The research where bonds are included as a variable is presented by Baek (2019), who investigates the linkages between the gold market and the stock market (S&P 500 index) and the bond market (iShares Core US Aggregate Bond ETF) in the period lasting from January 2009 to December 2018. Moreover, many additional economic and financial variables, such as the trade-weighted U.S. dollar index (TWDI, major currencies), industrial production index (IPI), consumer price index (CPI), and real personal income (RPI), are also included. The VAR/VECM approach is applied to conduct the causality and co-integration analysis. The research also investigates gold's predictive power and the impact of extreme returns. The author shows that gold returns are not co-integrated with stock and bond returns. While gold returns have unidirectional causalities with both, they are in opposite directions (from gold returns to stock returns and from bond returns to gold returns). Moreover, gold returns have some predictive power on subsequent short-term stock returns. It has also been proved that gold can better be a safe haven for stocks in a relative sense during temporary market downturns due to more simultaneous movements of gold and bond returns than stock returns. The results also confirm that gold returns have

some predictive power on subsequent future stock returns in subsequent short-term returns rather than subsequent medium- or long-term returns.

The set of four assets is considered by Chevallier and Ielpo (2013), who examine the nature of the cross-market linkages between commodities (gold, oil), stocks, and bonds. The variables included in the research are gold, WTI, S&P 500, GSCI sub-indices, and US 10-yearbond prices, respectively. The cointegration analysis is conducted during the entire period (1993–2011), as well as during the corresponding sub-periods (1993–2000) and (2000–2011). They consider testing the cointegration with and without structural breaks. Mixed results from the cointegration tests are reported depending on the variables examined and the analysis period adopted. Moreover, in many cases, the model estimates are unsatisfactory, i.e. insignificant or unstable in time. That is why they put in question the adequacy of applying the VECM approach and recommend considering other solutions, such as an econometric framework based on multivariate GARCH volatilities.

## Research methods

We analyse the linkages between four asset classes, including stocks, gold, crude oil, and bonds, from the perspective of the Polish capital market. The empirical data consists of the Warsaw Stock Exchange WIG Index (WIG), gold spot prices (GOLD\_PLN), Cushing, OK WTI Spot Price FOB (WTI\_PLN), and Treasury Bond-Spot Poland Index (TBSP.Index). In addition, we apply average US/PLN exchange rates published by the National Bank of Poland to express asset prices in the Polish zloty (PLN) domestic currency. The historical data are obtained from the following websites: Financial portal stooq.pl, the World Gold Council (WGC, 2023), the U.S. Energy Information Administration (EIA, 2023), and the National Bank of Poland. The sample covered the period from December 2006 to January 2023 (end-of-month), including 194 observations. All variables were transformed into logarithms before conducting further analysis and estimations.

We initiate our research process by examining basic descriptive statistics for logarithmic prices and testing the order of integration using the Augmented Dickey–Fuller (ADF) and Phillips–Perron tests for unit roots. Due to the non-stationarity of these variables, we calculate their first differences, defined as logarithmic returns, which are the stationary time series. In the next step, we test for cointegration of the logarithmic prices using Johansen's procedure that involves a test of the null hypothesis, assuming that there are no cointegrating vectors ( $H_0: r = 0$ ) in the VAR model versus the alternative hypothesis,  $H_1: r \leq 1$ , and so on (Johansen & Juselius, 1990). If the long-term relationship exists between the non-stationary variables, the model estimated based on the first differenced variables should be supplemented with the error correction mechanism (ECM). Such a model allows the inclusion of cointegrated variables' long- and short-term impacts.

We use the following p-dimensional VAR(k) model formulated in the general VECM form (see Juselius, 2006, pp. 61–63):

$$\Delta x_t = \Gamma_1^{(m)} \Delta x_{t-1} + \Gamma_2^{(m)} \Delta x_{t-2} + \cdots + \Gamma_{k-1}^{(m)} \Delta x_{t-k+1} + \Delta x_{t-1} + \Pi x_{t-m} + \Phi D_t + \varepsilon_t, \quad (1.1)$$

where:

$\Delta x_t$  – p x 1 dimensional vector of variables in the first differences, i.e. logarithmic returns (D.ln\_ith asset),

$x_{t-m}$  – p x 1 dimensional vector of logarithmic prices (ln\_ith asset),

$\Gamma_{k-1}^{(m)}$  – coefficients matrix of k-lagged logarithmic returns,

$\Pi$  – coefficients matrix of m-lagged logarithmic prices,  $\Pi = \alpha \beta$ ,

$\beta$  – coefficients matrix of the cointegrating vectors, reflecting the long-term impacts

$\alpha$  – coefficients matrix of the speed of adjustment to long-term equilibrium, reflecting the short-term impacts,

$D_t$  – vector of deterministic components,

$\Phi$  – coefficients matrix of vector  $D_t$ ,

$k$  – lag length of the VAR model,

$m$  – lag of the ECM term.

For p-variable model, the rank  $r$  of  $\Pi$  such as  $0 \leq r < p$ , informs about the number of linearly independent cointegrating relationships among the elements of vector  $x_t$ . This relationship describes the long-term equilibrium between non-stationary variables of vector  $x_t$ , and refers to the error correction mechanism (ECM) included in the VECM. If there is no cointegration relationship between logarithmic prices ( $r = 0$ ), the  $\Pi x_{t-m}$  equals 0 and can be omitted. This means that model (1.1) is estimated exclusively based on the first differences (logarithmic returns) (Becketti, 2013, p. 390). The VAR(k) estimates are used to analyse the Granger causality between logarithmic returns as proposed by Granger (1969).

Post-estimation tests involve checking the model's stability and the residuals' white noise. We apply the Lagrange multiplier test, Jarque–Bera test, skewness test, and kurtosis test (Becketti, 2013, pp. 414–415). Our approach involves using forecast-error variance decomposition (FEVDs) to gauge the influence of each orthogonalized shock on the overall forecast-error variance. Furthermore, we perform an IRF analysis to explore the impact of a particular shock (impulse) on the entire system. The IRF analysis entails plotting the impulse response function (IRF) of the coefficients  $\varphi_{jk}$  ( $i$ ) against time ( $i$ ), enabling us to depict the variables' response (Enders, 2010, p. 308). The robustness of the model is also checked with CUSUM test.

The main advantage of applying VAR/VECM models is that all variables can be treated symmetrically. This means we do not, *priori*, decide which variables are endo- and exogenous. Instead, we assume that a set of current and previous realisations of the other variables determines the time path of a given variable. In this case, we estimate a model consisting of p-equations where the selected variable is the independent one each time. The reasoning for such an approach was presented in detail by Sims (1980).

It is important to note that the results of a model can depend on the number of lags used during estimation. Also, analysing the variance decomposition of the forecast error using different orderings can affect the results. This is because the correlations between residuals obtained through subsequent model equations can significantly impact the outcomes (Enders, 2010, pp. 314–315). The method presented above is used to verify our research hypothesis.

## Results

We analyse the main characteristics of logarithmic prices as the variables used to calculate the logarithmic returns. Table 1 summarises basic statistics for time series at levels and first differences.

**Table 1.** The descriptive statistics for log prices of analysed assets in the period Dec 2006 to Jan 2023 (end-of-month)

| Variable       | Mean      | Std. Dev. | Variation coefficient | Skewness   | Kurtosis |
|----------------|-----------|-----------|-----------------------|------------|----------|
| ln_WIG         | 10.815850 | 0.2099449 | 1.94%                 | -1.1282840 | 5.048710 |
| ln_GOLD_PLN    | 8.388825  | 0.3916179 | 4.67%                 | -0.6728458 | 2.959605 |
| ln_WTI_PLN     | 5.458040  | 0.2920390 | 5.35%                 | -0.2303082 | 3.820409 |
| ln_TBSPIndex   | 7.311937  | 0.2205767 | 3.02%                 | -0.4522070 | 1.886596 |
| D.ln_WIG       | 0.001012  | 0.0598787 | 5916%                 | -0.5237709 | 5.440442 |
| D.ln_GOLD_PLN  | 0.007848  | 0.0568550 | 724%                  | 0.2702298  | 4.073328 |
| D.ln_WTI_PLN   | 0.003429  | 0.1117996 | 3260%                 | -0.8348561 | 14.54070 |
| D.ln_TBSPIndex | 0.003065  | 0.0124814 | 407%                  | 0.2298095  | 8.583282 |

Note: D.ln – first differences (D) of logarithmic asset prices (ln), i.e. logarithmic returns on assets.

Source: Author's own study.

As shown in Table 1, the crude oil logarithmic price is characterised by the highest variation coefficient, whereas the lowest is attributed to the stock index. The gold logarithmic price exhibits the highest deviation from the mean. Since all values in the skewness column are negative, the distribution of each variable under investigation is left-skewed. WIG and crude oil exhibit leptokurtic distributions; the bond index seems to have platykurtic distribution, while mesokurtic distribution is characteristic of gold logarithmic prices. Regarding logarithmic returns, the highest volatility is characteristic to gold returns and the lowest to bonds. However, deviation from the means is very high. All asset returns exhibit a platykurtic distribution.

The results regarding stationarity testing of logarithmic prices and their first differences defined as logarithmic returns on investment, using the augmented Dickey–Fuller test and Philips–Perron test for unit root, are presented in Table 2 and Table 3, respectively.

Regarding variables at levels, the null hypothesis is accepted at all significant levels in the case of gold and bonds, as the test statistics are larger algebraically

than any of the critical values and  $p$ -values exceed significance levels. At the same time, the unit root is confirmed for stocks and crude oil time series if we take 10% significant level. Finally, we assume that logarithmic prices are integrated of order one, I(1) since their first differences (logarithmic returns) are stationary regardless of the significance levels adopted.

**Table 2.** Augmented Dickey–Fuller test for unit root statistics

| Variable             | No. of obs./lags | Test statistic | MacKinnon's approximate, $p$ -value for $Z(t)$ |
|----------------------|------------------|----------------|--|
| At levels            |                  |                |  |
| ln_WIG               | 189/4            | -2.802*        | 0.0579   |
| ln_GOLD_PLN          | 181/12           | -2.421         | 0.3686   |
| ln_WTI_PLN           | 191/2            | -2.633*        | 0.0863   |
| ln_TBSPIndex         | 190/3            | -2.160         | 0.2211   |
| In first differences |                  |                |  |
| D.ln_WIG             | 189/3            | -5.259***      | 0.0000   |
| D.ln_GOLD_PLN        | 180/12           | -3.416**       | 0.0104   |
| D.ln_WTI_PLN         | 190/2            | -8.438***      | 0.0000   |
| D.ln_TBSPIndex       | 189/3            | -5.054***      | 0.0000   |

Note: H0: is rejected at significance levels: \*10%, \*\*5%, \*\*\*1%. D.ln – first differences (D) of logarithmic asset prices (ln), i.e. logarithmic returns on assets.

Source: Author's own study.

**Table 3.** Phillips–Perron test for unit root statistics

| Variable                | No. of obs./Newey–West lags | Test statistic |           | MacKinnon's approximate, $p$ -value for $Z(t)$ |
|-------------------------|-----------------------------|----------------|-----------|--|
|                         |                             | Z(rho)         | Z(t)      |  |
| At levels               |                             |                |           |  |
| ln_WIG                  | 193/4                       | -10.228        | -2.215    | 0.2008   |
| ln_GOLD_PLN             | 193/12                      | -2.708         | -1.538    | 0.5145   |
| ln_WTI_PLN              | 193/2                       | -16.237***     | -2.846*** | 0.0520   |
| ln_TBSPIndex            | 193/3                       | -1.671         | -2.035    | 0.2715   |
| In first differences*** |                             |                |           |  |
| D.ln_WIG                | 192/4                       | -178.503       | -12.410   | 0.0000   |
| D.ln_GOLD_PLN           | 192/12                      | -176.646       | -14.374   |  |
| D.ln_WTI_PLN            | 192/2                       | -152.497       | -11.582   | 0.0000   |
| D.ln_TBSPIndex          | 193/3                       | -175.918       | -12.400   | 0.0000   |

Note: H0: is rejected at significance levels: \*10%, \*\*5%, \*\*\*1%. D.ln – first differences (D) of logarithmic asset prices (ln), i.e. logarithmic returns on assets.

Source: Author's own study.

The Phillips–Perron test for unit root results show that the unit root is not confirmed only in the case of the logarithmic crude oil prices after assuming a 1% significance level. The null hypothesis cannot be rejected while considering the other three variables and at any significant levels applied. The results also suggest that all logarithmic returns seem stationary, which is consistent with the findings of the ADF test.

The market linkages are analysed based on stationary logarithmic returns to avoid spurious regression. Pearson's correlations between logarithmic returns calculated on a monthly basis are presented in Table 4.

**Table 4.** Pearson's correlation coefficient for logarithmic returns

| Variable       | D.ln_WIG            | D.ln_GOLD_PLN   | D.ln_WTI_PLN        | D.ln_TBSPIndex |
|----------------|---------------------|-----------------|---------------------|----------------|
| D.ln_WIG       | 1                   |                 |                     |                |
| D.ln_GOLD_PLN  | -0.2632*** (0.0002) | 1               |                     |                |
| D.ln_WTI_PLN   | 0.2251*** (0.0016)  | 0.0028 (0.9691) | 1                   |                |
| D.ln_TBSPIndex | 0.2053*** (0.0042)  | 0.0654 (0.3659) | -0.2291*** (0.0014) | 1              |

Note: *p*-value in brackets. H0: is rejected at significance levels: \*10%, \*\*5%, \*\*\*1%.

Source: Author's own study.

A moderate positive and statistically significant correlation is observed between WIG logarithmic returns and the other two variables, i.e. crude oil or bonds, respectively. At the same time, the moderate negative relationship refers to WIG and gold as well as the WTI and bond returns. While gold and WTI logarithmic returns change in the same direction, this relationship is weak and not statistically significant. A similar result is obtained concerning the gold and bond market relationship.

Estimating the model is proceeded by identifying the optimal number of lags (\*) and conducting the Johansen cointegration test to examine the existence of the long-term equilibrium between the stock index, gold, crude oil, and bonds logarithmic prices. The results are presented in Tables 5 and 6, respectively.

**Table 5.** The number of lags by information criterion of the VAR/VECM model

| Lag | LL      | LR      | df | p     | FPE                    | AIC       | HQIC      | SBIC      |
|-----|---------|---------|----|-------|------------------------|-----------|-----------|-----------|
| 0   | 165.522 |         |    |       | $2.10 \times 10^{-6}$  | -1.73679  | -1.70868  | -1.66742  |
| 1   | 1272.55 | 2214.1  | 16 | 0     | $1.70 \times 10^{-11}$ | -13.4683  | -13.3277* | -13.1214* |
| 2   | 1289.40 | 33.706  | 16 | 0.006 | $1.6 \times 10^{-11*}$ | -13.4775* | -13.2245  | -12.8531  |
| 3   | 1299.69 | 20.574  | 16 | 0.195 | $1.8 \times 10^{-11}$  | -13.416   | -13.0506  | -12.5142  |
| 4   | 1312.55 | 25.713  | 16 | 0.058 | $1.8 \times 10^{-11}$  | -13.3822  | -12.9043  | -12.2029  |
| 5   | 1330.19 | 35.288  | 16 | 0.004 | $1.8 \times 10^{-11}$  | -13.3999  | -12.8096  | -11.9431  |
| 6   | 1339.55 | 18.721  | 16 | 0.283 | $1.9 \times 10^{-11}$  | -13.3285  | -12.6257  | -11.5942  |
| 7   | 1357.17 | 35.236* | 16 | 0.004 | $1.9 \times 10^{-11}$  | -13.3459  | -12.5307  | -11.3342  |
| 8   | 1365.78 | 17.217  | 16 | 0.372 | $2.1 \times 10^{-11}$  | -13.2664  | -12.3387  | -10.9772  |

Note: \* preferred value of a statistics

Source: Author's own study.

The likelihood-ratio test (LR) suggests seven lags as optimal, while final prediction error (FPE) and Akaike's information criterion (AIC) are in favour of two lags. On the other hand, Hannan and Quinn's (HQIC) and Schwarz's Bayesian information criterion (SBIC) indicate that one lag is sufficient.

Due to the lack of unanimity in results, we consider three possible models, i.e. a VECM with two lags in a VAR representation and a VECM with one lag in a VAR representation, assuming one cointegrating relationship in both cases and a standard VAR in the first differences with one lag. As the test statistics of the Johansen test for cointegration can also be sensitive to the choice of trend specification and the lag length, we adopt different options and compare the results (two lags versus one lag in the underlying VAR model). The results of the two-lagged models are summarised in Table 6.

**Table 6.** The number of cointegrating vectors under different possible trend specifications of VECM with two lags in VAR representation (number of obs. = 192, Sample: Feb 2007 – Jan 2023, two lags)

| Trend specification              | H0        | LR statistics and Critical values |       |         |       | H0        | LR statistics and Critical values |       |        |       |
|----------------------------------|-----------|-----------------------------------|-------|---------|-------|-----------|-----------------------------------|-------|--------|-------|
|                                  |           | Trace                             | 5%    | Max     | 5%    |           | Trace                             | 5%    | Max    | 5%    |
| Unrestricted trend (trend)       | r(II) = 0 | 45.7344*                          | 54.64 | 26.4437 | 30.33 | r(II) = 2 | 7.0490                            | 18.17 | 6.8560 | 16.87 |
|                                  | r(II) = 1 | 19.2907                           | 34.55 | 12.2417 | 23.78 |           | 0.1931                            | 3.74  | 0.1931 | 3.74  |
| Restricted trend (rtrend)        | r(II) = 0 | 51.9858*                          | 62.99 | 26.5835 | 31.46 | r(II) = 2 | 13.0295                           | 25.32 | 7.4007 | 18.96 |
|                                  | r(II) = 1 | 25.4023                           | 42.44 | 12.3728 | 25.54 |           | 5.6288                            | 12.25 | 5.6288 | 12.52 |
| Unrestricted constant (constant) | r(II) = 0 | 47.5644                           | 47.21 | 26.4065 | 27.07 | r(II) = 2 | 8.8121                            | 15.41 | 6.6325 | 14.07 |
|                                  | r(II) = 1 | 21.1579*                          | 29.68 | 12.3458 | 20.97 |           | 2.1796                            | 3.76  | 2.1796 | 3.76  |
| Restricted constant (rconstant)  | r(II) = 0 | 61.8663                           | 53.12 | 31.5862 | 28.14 | r(II) = 2 | 12.2788                           | 19.96 | 9.9697 | 15.67 |
|                                  | r(II) = 1 | 30.2801*                          | 34.91 | 18.0013 | 22.00 |           | 2.3092                            | 9.42  | 2.3092 | 9.24  |

Note: \*null hypothesis (H0) is accepted at 5%; with one lag included, all Johansen test statistics indicate zero cointegration vectors.

Source: Author's own study.

In the case of unrestricted and restricted constant specification, the trace statistic suggests one cointegration vector, which is also confirmed by HQIC and AIC information criterion. At the same time, according to SBIC, there is no cointegration relationship between variables. Alternatively, the lack of long-term equilibrium is suggested in the case of Unrestricted trend (trend) and Restricted trend (rtrend) specifications.

We also address the issue of the nested VECM models in the analysis depending on the restrictions imposed (Table 7).

**Table 7.** Comparison of VECM model specifications based on the likelihood ratio test

| Assumption  | LR chi2(2) | Prob > chi2 |
|---|------------|-------------|
| H0: rtrend with two lags nested in trend with two lags ( $\tau = 0$ )         | 6.11       | 0.1063      |
| H0: constant with two lags nested in rtrend with two lags ( $\rho = 0$ )      | 0.18       | 0.6740      |
| H0: rconstant with two lags nested in constant with two lags ( $\gamma = 0$ ) | 9.12       | 0.0277**    |
| H0: constant with one lag nested in constant with two lags                    | 37.70      | 0.0017***   |

Note: H0: is rejected at significance levels: \*\*5%, \*\*\*1%;  $\gamma, \tau$  – linear trend and quadratic trend parameters incorporated in  $x_t$ , respectively;  $\nu, \rho$  – deterministic terms in the cointegrating equations representing the means and linear trends of those relationships, respectively.

Source: Author's own study.

After comparing these two VECM specifications, we decide to choose the Unrestricted constant type since we reject the null hypothesis stating that the model rconstant with two lags is nested in the model constant with two lags and accept the null of that the model constant with two lags is nested in model rtrend with two lags.

With respect to the final estimates of the selected VECM model specification, we find that all  $\beta$  coefficients in the long-term equation are statistically significant. Gold logarithmic prices negatively impact WIG compared to the positive influence of WTI and TBSP.Index. However, in the case of the short-term equations the analysis of signs and statistical significance of  $\alpha$  coefficients, reflecting the speed of adjustment to the long-term equilibrium, do not confirm the evidence for the short-term adjustment. In that case, we alternatively estimated the standard VAR model in the first differences with one lag presented in Table 8.

**Table 8.** The VAR model with one lag estimate, VAR(1)

| Equation       |                 | Coef.   | Std. Err. | z       | P> z      | [95% Conf. interval] |
|----------------|-----------------|---------|-----------|---------|-----------|----------------------|
| D.ln_WIG       | LD.ln_WIG       | 0.0736  | 0.0787    | 0.9400  | 0.3490    | -0.0806 0.2278       |
|                | LD.ln_GOLD_PLN  | -0.1856 | 0.0779    | -2.3800 | 0.0170**  | -0.3382 -0.0329      |
|                | LD.ln_WTI_PLN   | -0.0178 | 0.0406    | -0.4400 | 0.6620    | -0.0973 0.0618       |
|                | LD.ln_TBSPIndex | -0.0467 | 0.3688    | -0.1300 | 0.8990    | -0.7696 0.6762       |
|                | constant        | 0.0022  | 0.0044    | 0.5000  | 0.6190    | -0.0064 0.0107       |
| D.ln_GOLD_PLN  | LD.ln_WIG       | -0.0534 | 0.0755    | -0.7100 | 0.4790    | -0.2015 0.0946       |
|                | LD.ln_GOLD_PLN  | -0.0472 | 0.0748    | -0.6300 | 0.5280    | -0.1938 0.0994       |
|                | LD.ln_WTI_PLN   | -0.0540 | 0.0390    | -1.3900 | 0.1660    | -0.1304 0.0224       |
|                | LD.ln_TBSPIndex | 0.3043  | 0.3542    | 0.8600  | 0.3900    | -0.3899 0.9985       |
|                | constant        | 0.0072  | 0.0042    | 1.7200  | 0.0850    | -0.0010 0.0154       |
| D.ln_WTI_PLN   | LD.ln_WIG       | 0.4812  | 0.1445    | 3.3300  | 0.0010*** | 0.1979 0.7644        |
|                | LD.ln_GOLD_PLN  | 0.0848  | 0.1431    | 0.5900  | 0.5530    | -0.1956 0.3653       |
|                | LD.ln_WTI_PLN   | 0.0850  | 0.0746    | 1.1400  | 0.2540    | -0.0611 0.2312       |
|                | LD.ln_TBSPIndex | -0.8813 | 0.6777    | -1.3000 | 0.1930    | -2.2095 0.4469       |
|                | constant        | 0.0047  | 0.0080    | 0.5900  | 0.5560    | -0.0110 0.0205       |
| D.ln_TBSPIndex | LD.ln_WIG       | -0.0103 | 0.0166    | -0.6200 | 0.5360    | -0.0427 0.0222       |
|                | LD.ln_GOLD_PLN  | -0.0181 | 0.0164    | -1.1000 | 0.2700    | -0.0502 0.0141       |
|                | LD.ln_WTI_PLN   | -0.0136 | 0.0085    | -1.5900 | 0.1110    | -0.0304 0.0031       |
|                | LD.ln_TBSPIndex | 0.0747  | 0.0777    | 0.9600  | 0.3360    | -0.0775 0.2270       |
|                | constant        | 0.0030  | 0.0009    | 3.2900  | 0.0010*** | 0.0012 0.0048        |

Note: L – lagged value of D.ln; D.ln – first differences (D) of logarithmic asset prices (ln), i.e. logarithmic returns on assets; asterisks \*, \*\* and \*\*\* represent significance level at 10, 5, and 1%, respectively.

Source: Author's own study.

Referring to the VAR model, only the coefficient associated with lagged gold returns is statistically significant in the case of the first equation. In contrast, in the second one, all coefficients are not statistically different from zero at 5%. After considering crude oil returns as an independent variable, the parameter for lagged stock returns is only statistically significant at 1%. Finally, no statistically significant effect of lagged returns on bond returns is indicated.

A summary of the results regarding eigenvalue stability condition, autocorrelation, and normality tests is presented in Tables 9 and 10. The estimated VAR model satisfies the stability condition since all the eigenvalues lie inside the unit circle. There is also no proof of autocorrelated errors by the Lagrange-multiplier test. We also report the evidence of non-normality of residuals for all equations. The skewness test accepts the null hypothesis for gold and bond index equations at 10% or the stock index at 5%.

**Table 9.** The Lagrange-multiplier test results and eigenvalues for the VAR model

| lag                  | chi2    | df                   | Prob > chi2           |
|----------------------|---------|----------------------|-----------------------|
| 1                    | 18.9577 | 16                   | 0.27086 <sup>c)</sup> |
| 2                    | 17.3353 | 16                   | 0.36423 <sup>c)</sup> |
| Eigenvalue           | Modulus | Eigenvalue           | Modulus               |
| 0.2388               | 0.2388  | -0.0279 - 0.1237263i | 0.1268                |
| -0.0279 + 0.1237263i | 0.1268  | 0.0031               | 0.0031                |

Note: H0 is accepted at <sup>a)</sup> 1%, <sup>b)</sup> 5%, and <sup>c)</sup> 10%, respectively.

Source: Author's own study.

**Table 10.** Tests for normality of VAR equations residuals

| Jarque-Bera test |          |          |    |                      |
|------------------|----------|----------|----|----------------------|
| Equation         |          | chi2     | df | Prob > chi2          |
| D.ln_WIG         |          | 29.276   | 2  | 0.0000               |
| D.ln_GOLD_PLN    |          | 9.337    | 2  | 0.0094               |
| D.ln_WTI_PLN     |          | 363.515  | 2  | 0.0000               |
| D.ln_TBSPIndex   |          | 210.809  | 2  | 0.0000               |
| ALL              |          | 612.938  | 8  | 0.0000               |
| Equation         | Skewness | chi2     | df | Prob > chi2          |
| D.ln_WIG         | -0.3143  | 3.1610   | 1  | 0.0754 <sup>b)</sup> |
| D.ln_GOLD_PLN    | 0.2425   | 1.8810   | 1  | 0.1702 <sup>c)</sup> |
| D.ln_WTI_PLN     | -0.3554  | 4.0420   | 1  | 0.0444 <sup>a)</sup> |
| D.ln_TBSPIndex   | 0.1229   | 0.4840   | 1  | 0.4868 <sup>c)</sup> |
| ALL              |          | 9.5680   | 4  | 0.0484 <sup>a)</sup> |
| Equation         | Kurtosis | chi2     | df | Prob > chi2          |
| D.ln_WIG         | 4.8067   | 26.1150  | 1  | 0.0000               |
| D.ln_GOLD_PLN    | 3.9654   | 7.4560   | 1  | 0.0063               |
| D.ln_WTI_PLN     | 9.7033   | 359.4730 | 1  | 0.0000               |
| D.ln_TBSPIndex   | 8.1274   | 210.3260 | 1  | 0.0000               |
| ALL              |          | 603.3690 | 4  | 0.0000               |

Note: H0 is accepted at <sup>a)</sup> 1%, <sup>b)</sup> 5%, and <sup>c)</sup> 10%, respectively. D.ln – first differences (D) of logarithmic asset prices (ln), i.e. logarithmic returns on assets.

Source: Author's own study.

We also performed the cumulative sum test for parameters stability (CUSUM). Based on the results presented in Table 11, there is no ground to reject the null hypothesis of structural break at 5% as test statistics are less than 5% critical value.

**Table 11.** CUSUM test results

| Equation       | Statistic | Test Statistic | Critical Value |        |        |
|----------------|-----------|----------------|----------------|--------|--------|
|                |           |                | 1%             | 5%     | 10%    |
| D.ln_WIG       | recursive | 0.8078         | 1.143          | 0.9479 | 0.8500 |
| D.ln_GOLD_PLN  | recursive | 0.4401         | 1.143          | 0.9479 | 0.8500 |
| D.ln_WTI_PLN   | recursive | 0.4497         | 1.143          | 0.9479 | 0.8500 |
| D.ln_TBSPIndex | recursive | 0.5693         | 1.143          | 0.9479 | 0.8500 |

Note: H0: No structural break is accepted at 5%. D.ln – first differences (D) of logarithmic asset prices (ln), i.e. logarithmic returns on assets.

Source: Author's own study.

The summary of the Granger causality test is presented in Table 12. Since the null hypothesis assuming the lack of interrelation between logarithmic returns (D.ln) is being tested, the direction of the crossed arrows reflects the direction of non-causality between the variables. After rejecting the null hypothesis, we conclude that the gold returns are the Granger cause of the stock returns. Similarly, the stock returns have an impact on crude oil. All identified relationships are unidirectional and characterise the nature of dependencies between analysed markets in the short term.

**Table 12.** The Granger causality direction

| H0: no Granger causality                   | chi2    | df | Prob > chi2 |
|--|---------|----|-------------|
| Equation D.ln_WIG                          |         |    |             |
| D.ln_GOLD_PLN $\rightarrow$ D.ln_WIG       | 5.6784  | 1  | 0.017**     |
| D.ln_WTI_PLN $\rightarrow$ D.ln_WIG        | 0.1916  | 1  | 0.662       |
| D.ln_TBSPIndex $\rightarrow$ D.ln_WIG      | 0.0160  | 1  | 0.899       |
| ALL  | 6.2448  | 3  | 0.100       |
| Equation D.ln_GOLD.PLN                     |         |    |             |
| D.ln_WIG $\rightarrow$ D.ln_GOLD.PLN       | 0.5007  | 1  | 0.479       |
| D.ln_WTI_PLN $\rightarrow$ D.ln_GOLD.PLN   | 1.9193  | 1  | 0.166       |
| D.ln_TBSPIndex $\rightarrow$ D.ln_GOLD.PLN | 0.7383  | 1  | 0.39        |
| ALL  | 4.5258  | 3  | 0.210       |
| Equation D.ln_WTI_PLN                      |         |    |             |
| D.ln_WIG $\rightarrow$ D.ln_WTI_PLN        | 11.087  | 1  | 0.001***    |
| D.ln_GOLD_PLN $\rightarrow$ D.ln_WTI_PLN   | 0.3515  | 1  | 0.553       |
| D.ln_TBSPIndex $\rightarrow$ D.ln_WTI_PLN  | 1.6913  | 1  | 0.193       |
| ALL  | 11.421  | 3  | 0.010       |
| Equation D.ln_TBSPIndex                    |         |    |             |
| D.ln_WIG $\rightarrow$ D.ln_TBSPIndex      | 0.38309 | 1  | 0.536       |
| D.ln_GOLD_PLN $\rightarrow$ D.ln_TBSPIndex | 1.2164  | 1  | 0.270       |
| D.ln_WTI_PLN $\rightarrow$ D.ln_TBSPIndex  | 2.5389  | 1  | 0.111       |
| ALL  | 4.8605  | 3  | 0.182       |

Note: H0: is rejected at significance levels: \*\*5%, \*\*\*1%; D.ln – first differences (D) of logarithmic asset prices (ln), i.e. logarithmic returns on assets.

Source: Author's own study.

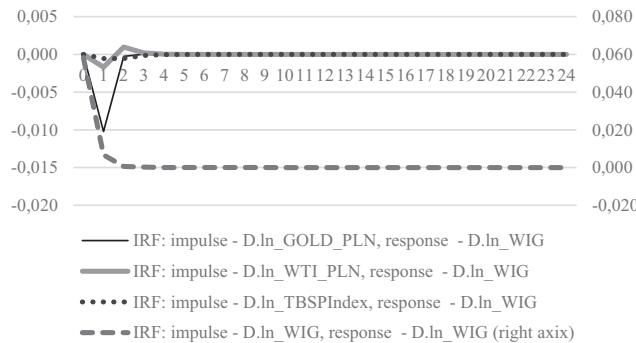
Panels A, B, C, and D of Table 13 report the FEVDs for the stock, gold, crude oil, and bonds. As the WIG logarithmic returns are placed first in adopted ordering, 100% of the forecast error variance in the first step is attributed to the error in the WIG equation. In comparison, twenty-four steps ahead, about 97% is still explained by own shocks of stock returns, nearly 3% by the error in the gold returns, and less than 1% is associated with crude oil and bond logarithmic returns shocks. This is consistent with the Granger test results. The gold returns contribute to the one-step ahead, FEVD equals 91.73%, while the impact of WIG returns on the uncertainty in the gold equation is less than 8.3%. The prediction errors of the crude oil equation are mainly due to their disturbance and vary from 94 to 87.4%, while from 5 to 10.4% is attributed to WIG shocks. Referring to the fourth equation, almost 88% of the forecast-error variance in the first step is attributed to the shocks in the bond equation, whereas more than 11% is split between crude oil and stocks, and the contribution of gold is less than 2%. In the applied ordering, the error variance in all equation forecasts is mainly due to uncertainty in respective equations.

**Table 13.** Forecast-error variance decomposition (FEVD) of VAR equations  
(ordering D.ln\_WIG, D.ln\_GOLD\_PLN, D.ln\_WTI\_PLN, D.ln\_TBSPIndex)

| Logarithmic returns | Panel A: Response D.ln_WIG     |       |        |           | Panel B: Response D.ln_GOLD_PLN  |        |       |           |
|---------------------|--------------------------------|-------|--------|-----------|----------------------------------|--------|-------|-----------|
|                     | WIG                            | GOLD  | WTI    | TBSPIndex | WIG                              | GOLD   | WTI   | TBSPIndex |
| Step/Impulse        |                                |       |        |           |                                  |        |       |           |
| 1                   | 100.00%                        | 0.00% | 0.00%  | 0.00%     | 8.27%                            | 91.73% | 0.00% | 0.00%     |
| 2                   | 96.97%                         | 2.94% | 0.08%  | 0.01%     | 8.34%                            | 89.91% | 1.36% | 0.38%     |
| 3                   | 96.94%                         | 2.94% | 0.11%  | 0.02%     | 8.43%                            | 89.79% | 1.38% | 0.40%     |
| 4–24                | 96.94%                         | 2.94% | 0.11%  | 0.02%     | 8.44%                            | 89.79% | 1.38% | 0.40%     |
| Logarithmic returns | Panel C: Response D.ln_WTI_PLN |       |        |           | Panel D: Response D.ln_TBSPIndex |        |       |           |
| Step/Impulse        | WIG                            | GOLD  | WTI    | TBSPIndex | WIG                              | GOLD   | WTI   | TBSPIndex |
| 1                   | 4.92%                          | 1.16% | 93.92% | 0.00%     | 3.97%                            | 0.99%  | 7.28% | 87.76%    |
| 2                   | 10.20%                         | 1.23% | 87.74% | 0.83%     | 3.98%                            | 1.65%  | 8.83% | 85.54%    |
| 3                   | 10.42%                         | 1.34% | 87.40% | 0.84%     | 4.08%                            | 1.65%  | 8.83% | 85.44%    |
| 4–24                | 10.42%                         | 1.35% | 87.39% | 0.84%     | 4.09%                            | 1.65%  | 8.83% | 85.43%    |

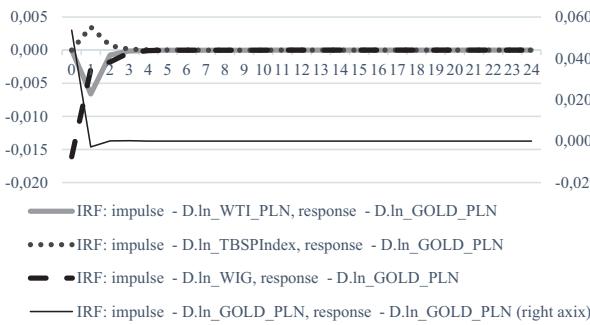
Source: Author's own study.

The analysis also involves the IRF functions. Assuming the given order of equations is necessary to adopt the Cholesky decomposition and to retrieve the structural disturbances from the residuals of the estimated VAR model. The values of the impulse response function caused by shocks in given logarithmic rates of return according to the order of equations: stock (D.ln\_WIG), gold (D.ln\_GOLD\_PLN), crude oil (D.ln\_WTI\_PLN), and bond returns (D.ln\_TBSPIndex) are depicted in Figures 1–4. The forecasting horizon covers 24 months.



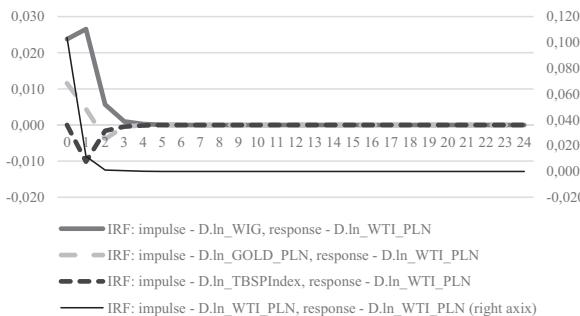
**Figure 1.** IFR functions: response of rate of return on stock (D.ln\_WIG) to shocks (impulses) in stock (D.ln\_WIG), gold (D.ln\_GOLD\_PLN), crude oil (D.ln\_WTI\_PLN), and bond returns (D.ln\_TBSPIndex)

Source: Author's own study.



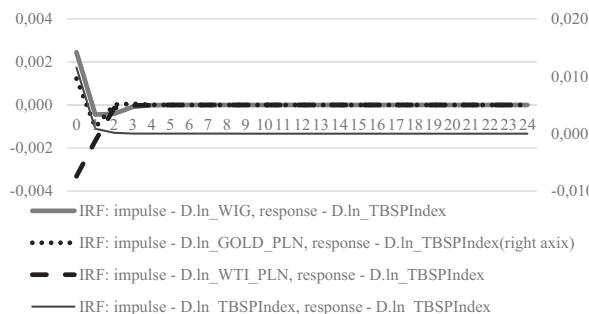
**Figure 2.** IFR functions: response of rate of return on gold (D.ln\_GOLD\_PLN) to shocks (impulses) in stock (D.ln\_WIG), gold (D.ln\_GOLD\_PLN), crude oil (D.ln\_WTI\_PLN), and bond returns (D.ln\_TBSPIndex)

Source: Author's own study.



**Figure 3.** IFR functions: response of rate of return on crude oil (D.ln\_WTI\_PLN) to shocks (impulses) in stock (D.ln\_WIG), gold (D.ln\_GOLD\_PLN), crude oil (D.ln\_WTI\_PLN), and bond returns (D.ln\_TBSPIndex)

Source: Author's own study.



**Figure 4.** IRF functions: response of rate of return on bond returns (D.In\_TBSPIndex) to shocks (impulses) in stock (D.In\_WIG), gold (D.In\_GOLD\_PLN), crude oil (D.In\_WTI\_PLN), and bond returns (D.In\_TBSPIndex)

Source: Author's own study.

Based on the IRF chart patterns, individual variables' positive and negative reactions to shocks can be observed. As the time horizon increases, the values of the impulse response functions converge to zero. The most extended period of disorders lasts two to four months, after which they quickly disappear. As the impulses suppress rapidly, the shocks do not cause substantial fluctuations in the rates of return. The results confirm the stability of the system and the independence of returns rates.

## Discussion

We find a cointegrating relationship between the gold and the stock market prices in Poland, like Al-Ameer et al. (2018) for the Frankfurt Stock Exchange. In contrast, we also indicate that gold returns are the Granger cause of the stock returns, which was not the case in the German financial market they analysed. The same direction of causality as presented by our findings was identified by other researchers, e.g. Tiwari et al. (2019) for the wide range of countries they examined. The results can also depend on the selected period and market benchmarks, as presented by Mamcarz (2021). The correlation between these two markets in Poland is negative, which stays in line with the assumption of treating these two asset classes as alternative forms of capital investments; however, positive linkages are also possible, as the authors mentioned above proved.

Referring to stock-bond interrelations, we indicate no causal linkages between these markets, which contradicts the results obtained by Zakamulin and Hunnes (2021). However, the results cannot be fully comparable as they cover the U.S. market, and the period under analysis included in their study is exceptionally long, even if we take the sub-periods. Our findings are also opposite to the results characteristic to the Chinese market during the financial crisis when the mutual linkages were indicated, for instance, by Deng et al. (2022).

The linkages observed between the Polish stocks index and the crude oil prices are positive, which is consistent with the results obtained by Chkili (2022) based on the Islamic financial market. Moreover, the relationship between the crude oil and gold market is negative, which is typical for both findings.

We observe the cointegration of the markets under investigation in Poland. However, the lack of long-term equilibrium between gold, stock, and bond returns combined with the other financial variables is also possible, as Baek (2019) presented while examining the U.S. assets market. Nonetheless, the causality between gold and stock returns is still confirmed in both markets. Chevalier and Ielpo (2013) also indicate mixed results concerning cointegration and show the limitation of the VECM approach.

## Conclusions

We show that the markets under analysis are cointegrated, meaning a long-term relationship exists between the financial asset prices considered in Poland. The relationship is significant since all coefficients are statistically different from zero. We observe the negative impact of gold logarithmic prices on the stock index WIG, showing the opposite relationship between their price developments. On the other hand, the effect of crude oil and bonds on the stock market is positive. Although the cointegration of the examined markets is observed in Poland, the short-term adjustment is not reached if the speed of adjustment coefficient  $\alpha$  is not statistically significant and does not have the expected sign required for the system to return to equilibrium.

Referring to rates of return, the positive correlation between WIG logarithmic returns and the other two variables, i.e. crude oil or bonds, respectively, is moderate and statistically significant. While a moderate negative relationship is observed between WIG and gold, similarly, WTI and bond returns also change in the opposite direction. Moreover, the relationship between gold – WTI and gold-bond markets is weak and not statistically significant.

In the short-term, stock returns can be explained by the gold price changes due to the Granger causality running from gold to the stock market. In contrast, stock returns Granger cause the crude oil returns. No causal linkages are confirmed in the other cases, which means that variables are independent from this point of view. The research hypothesis of the impact of gold, crude oil, and bonds on the stock market is only valid for the gold-stock causal relationship. Forecast-error variance decomposition of VAR equations confirms that all variables are explained by their shocks from 85 to 97% in the 24-month horizon.

Based on IRF functions, positive and negative reactions of individual return rates to shocks can be observed. The impacts converge to zero as the time horizon increases. The disturbances disappear after two to four months. The findings confirm the system's stability and the returns' relatively strong independence.

The results suggest that Polish investors can combine stocks and gold, as they are interrelated alternative investments. Crude oil and bonds also show diversifying properties relative to each other in terms of correlation, which, however, is not confirmed by the Granger test, implying independence. The positive relationship between WIG returns and the other two variables, i.e. crude oil or especially bonds, is undesirable while selecting portfolio components.

A limitation of the conducted research is that the base date of the bond index is December 29, 2006, which was set as the starting point of the data samples. The literature review shows that the results may depend on the chosen analysis period. Data availability for a more extended period would also enable the examination of sub-periods to be considered. This will be an area for further research in the future.

## References

Al-Ameer, M., Hammad, W., Ismail, A., & Hamdan, A. (2018). The relationship of the gold price with the stock market: The case of Frankfurt Stock Exchange. *International Journal of Energy Economics and Policy*, 8(5), 357–371.

Baek, C. (2019). How are gold returns related to stock or bond returns in the U.S. market? Evidence from the past 10-year gold market. *Applied Economics*, 50(51), 5490–5497.  
<https://doi.org/10.1080/00036846.2019.1616062>

Becketti, S. (2013). *Introduction to Time Series Using Stata*. Stata Press Publication.

Beckmann, J., Berger, T., & Czudaj, R. (2015). Does gold act as a hedge or a safe haven for stocks? A smooth transition approach. *Economic Modelling*, 48, 16–24. <https://doi.org/10.1016/j.econmod.2014.10.044>

Chevallier, J., & Ielpo, F. (2013). Cross-market linkages between commodities, stocks and bonds. *Applied Economics Letters*, 20(10), 1008–1018. <http://dx.doi.org/10.1080/13504851.2013.772286>

Chkili, W. (2022). The links between gold, oil prices, and Islamic stock markets in a regime-switching environment. *Eurasian Economic Review*, 12, 169–186. <https://doi.org/10.1007/s40822-022-00202-y>

Deng, C., Su, X., Wang, G., & Peng, C. (2022). The existence of flight-to-quality under extreme conditions: Evidence from a nonlinear perspective in Chinese stocks and bonds' sectors. *Economic Modelling*, 105895. <https://doi.org/10.1016/j.econmod.2022.105895>

Diebold, F.X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57–66.  
<https://doi.org/10.1016/j.ijforecast.2011.02.006>

Diebold, F.X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1), 119–134.  
<https://doi.org/10.1016/j.jeconom.2014.04.012>

EIA. (2023). Petroleum & other liquids, spot prices. [http://www.eia.gov/dnav/pet/pet\\_pri\\_spt\\_s1\\_d.htm](http://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm)

Enders, W. (2010). *Applied Econometric Time Series*. Wiley & Sons.

Enwereuzoh, P.A., Odei-Mensah, J., & Junior, P.O. (2021). Crude oil shocks and African stock markets. *Research in International Business and Finance*, 55, 101346.  
<https://doi.org/10.1016/j.ribaf.2020.101346>

Golitsis, P., Gkasis, P., & Bel, S.K. (2022). Dynamic spillovers and linkages between gold, crude oil, S&P 500, and other economic and financial variables. Evidence from the USA. *The North American Journal of Economics and Finance*, 63, 101785. <https://doi.org/10.1016/j.najef.2022.101785>

Granger, C. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, 37(3), 424–438. <https://doi.org/10.2307/1912791>

Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration with applications to the demand for money. *Oxford Bulletin of Economics & Statistics*, 52(2), 169–210. <https://doi.org/10.1111/j.1468-0084.1990.mp52002003.x>

Juselius, K. (2006). *The Cointegrated VAR Model: Methodology and Applications*. Oxford University Press.

Kusideł, E. (2000). *Modele wektorowo-autoregresyjne VAR: metodologia i zastosowania*. Absolwent.

Mamcarz, K. (2018). Podstawowe klasy aktywów jako determinanaty ceny złota w okresie długim. Analiza zależności. *Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu*, 533, 160–170. <https://doi.org/10.15611/pn.2018.533.16>

Mamcarz, K. (2021). Granger causality between stock and gold returns – evidence from Poland, Hungary and the Czech Republic. *Annales Universitatis Mariae Curie-Skłodowska, sectio H – Oeconomia*, 55(3), 67–80. <https://doi.org/10.17951/h.2021.55.3.67-80>

Mensi, W., Reboredo, J., & Ugolin, A. (2021). Price-switching spillovers between gold, oil, and stock markets: Evidence from the USA and China during the COVID-19 pandemic. *Resources Policy*, 73, 102217. <https://doi.org/10.1016/j.resourpol.2021.102217>

NBP. (2023). *Historic average exchange rates – table A*. <https://nbp.pl/en/statistic-and-financial-reporting/rates/archive-table-a-csv-xls/>

Sekuła, P. (2018). The causal relationships between WIG20 and PLN. *Annales Universitatis Mariae Curie-Skłodowska, sectio H – Oeconomia*, 52(4), 73–81. <https://doi.org/10.17951/h.2018.52.4.73-81>

Sims, C. (1980). Macroeconomics and reality. *Econometrica*, 48(1). <https://doi.org/10.2307/1912017>

Singh, D. (2014). The dynamics of gold prices, crude oil prices and stock index comovements: Cointegration evidence of India. *Finance India*, 28(4), 1265–1274.

Stooq.pl. (2023). *Historical data Treasury BondSpot Poland Index (^TBSP)*. <https://stooq.pl/q/d/?s=%5Etbsp&c=0&i=m>

Tiwari, A. K., Adewuyi, A., & Roubaud, D. (2019). Dependence between the global gold market and emerging stock markets (E7+1): Evidence from Granger causality using quantile and quantile-on-quantile regression methods. *The World Economy*, 42(7), 2172–2214. <https://doi.org/10.1111/twec.12775>

Tursoy, T., & Faisal, F. (2018). The impact of gold and crude oil prices on stock market in Turkey: Empirical evidences from ARDL bounds test and combined cointegration. *Resources Policy*, 55, 49–54. <https://doi.org/10.1016/j.resourpol.2017.10.014>

WGC. (2023). *Gold spot prices*. <https://www.gold.org/goldhub/data/gold-prices>

Wu, Y., Zhou, X. (2015). VAR Models: Estimation, inferences, and applications. In C.F. Lee & J. Lee (Eds.), *Handbook of Financial Econometrics and Statistics* (pp. 2077–2091). Springer. [https://doi.org/10.1007/978-1-4614-7750-1\\_76](https://doi.org/10.1007/978-1-4614-7750-1_76)

Zakamulin, V., & Hunnes, J.A. (2021). Stock earnings and bond yields in the US 1871–2017: The story of a changing relationship. *The Quarterly Review of Economics and Finance*, 79, 182–197. <https://doi.org/10.1016/j.qref.2020.05.013>