ISSN: 2029-4913 / eISSN: 2029-4921

TECHNOLOGICAL and ECONOMIC DEVELOPMENT of ECONOMY

2025
Volume 31
Issue 6
Pages 1720–1748
https://doi.org/10.3846/tede.2025.23122

# FUEL PRICES AND ECONOMIC ACTIVITY: TIME AND FREQUENCY ANALYSIS FOR SELECTED EUROPEAN COUNTRIES

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**Article History:**
- received 19 July 2023
- accepted 02 December 2024
- first published online 15 April 2025

**Abstract.** The effects of fuel prices on economic activity are still being investigated, as oil and gas are critical inputs in the production process. This study examines the relationship between fuel prices and macroeconomic aggregates both in the time domain and frequency domain in three selected countries of Germany and Poland as net oil importers and Norway as a net oil exporter for the period 1995Q1–2021Q3. The causal relationships between these macroeconomic variables are first examined using a conventional Granger causality test for the time domain and then the Breiutung–Candelon test based on the vector autoregression model for the frequency domain, which are estimated separately for the long-term, business cycle, and short-term components obtained by applying the boosted Hodrick–Prescott filter. This study demonstrates that the predictability of fuel prices for macroeconomic aggregates differs across various frequencies. Although the patterns of causality differ across countries depending on whether it is oil-importing or oil-exporting and the level of economic development and energy mix, this relationship is found to be important for slowly and fast fluctuating components but to different degrees in each country.

**Keywords:** boosted HP filter, frequency domain, causality patterns, economic activity, fuel prices.

**JEL Classification:** E31, E32, Q31, Q43.

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## 1. Introduction

Since the 1970s, when oil prices rose sharply, economists have been investigating the relationship between oil prices and macroeconomic variables (Burbidge & Harrison, 1984; Hamilton, 1983, 2003; Katayama, 2013; Kilian, 2009). This relationship is of considerable economic importance, as energy resources (oil and gas being the highest share) and energy costs constitute indispensable factors in the production process and growth (Stern, 2004). As a result, there have been many studies attempting to draw the causal relationship between oil prices and macroeconomic activities. Oil price movements may influence the economy directly and indirectly through different transmission mechanisms varying from the supply effect to demand effect to the terms of trade effect and wealth effect (Bretschger, 2015; Brown & Yücel, 2002; Ferderer, 1996; Jo et al., 2019; Kilian, 2009; Lardic & Mignon, 2006, 2008; Sill, 2007). On the supply side, an increase in oil prices directly raises production costs as crude oil is an input for production and thereby leads to a slowdown in production and productivity.

On the demand side, higher oil prices create inflationary pressures, and as the real income available for consumption falls, demand decreases. On the terms of trade, the oil price hike appreciates (depreciates) the exchange rates of the oil-exporting (oil-importing) countries by improving (deteriorating) their terms of trade conditions and this results in wealth transfers from oil-importing to oil-exporting countries (Krugman, 1980). Moreover, other multidimensional negative and indirect effects occur that result from rising energy costs, such as decreased investments, reduced stock prices and increased unemployment (Bretschger, 2015; Jo et al., 2019). Although there is still debate about the mechanisms and degree of impact of oil price shocks, most studies have found that oil prices have a significant impact on main macroeconomic variables such as economic growth, inflation levels and the exchange rate (e.g., Blanchard & Gali, 2007; Brown & Yücel, 1999; Cunado & Perez de Gracia, 2005; Lardic & Mignon, 2008; Lizardo & Mollick, 2010; Raheem Ahmed et al., 2017; Wang et al., 2023).

The causal pattern of oil price-macroeconomy relationship may vary depending on the country's status (oil-importing or oil-exporting country), its general economic performance, and its energy policy (Mo et al., 2019; Nasir et al., 2018). Furthermore, the economic effects of oil prices may be different according to the econometric methods applied, starting from traditional econometric techniques in the time domain (vector autoregressive models, VAR, vector error correction models, VECM, Granger causality) assuming the linear and symmetric relationship between oil prices and key macroeconomic variables, through nonlinear specifications of VAR models (e.g., Jiménez-Rodríguez & Sánchez, 2005) and more advanced nonlinear econometric techniques (like Markov-switching models or multivariate threshold models (e.g., Cologni & Manera, 2009; Huang et al., 2005) – till the analysis in the frequency domain – as an alternative approach to nonlinearity and asymmetry – allowing the oil price-macroeconomy relationship be different across various frequencies (Kırca et al., 2020; Wei, 2013; Wei & Guo, 2016). Our study draws on both approaches, i.e., in both the time domain and frequency domain, with more attention focused on the latter.

This study analyzes the relationship between fuel prices (oil and gas) and economic activity represented by fundamental macroeconomic variables (economic growth, inflation, and exchange rate) in both the time domain and frequency domain to evaluate the predictive power of shocks in fuel prices for variables describing a country's economic performance, in terms of slowly or quickly fluctuating components, and also to what extent it is dependent on the country's status (oil-importing or oil-exporting). To do so, we analyze the relations between fuel prices (oil and gas) and different macroeconomic variables using data from the 1995Q1–2021Q3 period for two oil-importing countries (Germany and Poland) and one oil-exporting country (Norway). This issue is investigated applying the conventional Granger causality test based on the VAR model (Geweke, 1982) and the frequency causality measure proposed by Breitung and Candelon (2006), Hosoya (2001). We also conduct various robustness tests on the frequency domain causality analysis by calculating the coherence coefficient for pairs of series that are detrended with the boosted Hodrick–Prescott (bHP) filter.

This study makes three major contributions to the literature. First, the research is conducted with a Vector Auto Regression model for all five main relevant variables: oil and gas prices, inflation, exchange rate and economic growth, while the predominant existing literature has focused on binary relationships: oil price and inflation, either oil price and exchange rate or oil price and economic growth, with few exceptions (e.g., Ahmad et al., 2022; Basnet & Upadhyaya, 2015; Huang & Guo, 2007; Iwayemi & Fowowe, 2011; Ji et al., 2015), although these studies concern only the relationships in the time domain. To the best of authors' knowledge, this is the first work to comprise the examination of all these variables on a group of oil-exporting and oil-importing countries in both the time and frequency domain.

Second, we examine the multivariate pattern of causal linkages separately across three different frequency components (long-term, business cycle term and short-term) by employing a frequency domain causality test (Breitung & Candelon, 2006) – while most studies focus on long-term and short-term components – to reveal differences in the causality patterns through which oil and gas prices affect the economic performance for selected oil-importing and oil-exporting countries (Germany, Poland, Norway), comparing these results with those determined examining the time domain (as a benchmark). As the existence of frequency dependence implies that the relationship between oil (gas) prices and fundamental macroeconomic variables is nonlinear (Ashley & Verbrugge, 2009), then examining the effect of oil (gas) prices on economic performance across different frequency bands can be viewed as an alternative approach with regard to nonlinear or asymmetric econometric models in the time domain. However, unlike the time domain analysis, the frequency domain analysis provides outcomes in terms of different timings and frequencies where causality exists (Olayungbo, 2019) and therefore gives a more in-depth comprehension of the impact of oil (gas) prices on the economic performance than in the time domain. The main rationale for this approach is to obtain a more precise evaluation of differential impacts of oil (gas) prices, according to specific country characteristics, on the economic growth, inflation and exchange rate in each country. The relevance for policy and decision makers is evident: the formulation of policies should be tailored to the differentiated effects of oil (gas) prices on economic performance depending on the long, business cycle and short-term perspective in order to alleviate the adverse effects of oil and gas price changes and better predict future changes in economic activity.

Third, the causality analysis for oil (gas) prices-macroeconomy relationship in the time and frequency domains is conducted for variables detrended with the boosted Hodrick-Prescott (bHP) filter, newly developed by Phillips and Shi (2021), which makes it possible to identify patterns of causality without distorting the outcomes with spurious cycles as is the case with other filters commonly applied to detrend times series, i.e. a differential filter causing a distortion of high frequency bands or the Hodrick-Prescott (HP) filter having the following main disadvantages: the presence of spurious cycles, the bias at the sample end, the ad hoc hypotheses for smoothing parameters. This work is so far a sole one applying the bHP filter in a comprehensive framework for examining the causal effects of oil (gas) prices on the key macroeconomic variables in both the time and frequency domains and providing the more precise recommendations for policy makers.

The remainder of this paper is organized as follows. Section 2 briefly details the related literature on relationships between oil prices and macroeconomic aggregates. Section 3 presents the econometric methods used in the study. Section 4 introduces the empirical results of our analysis, and Section 5 presents the policy implications and concludes the paper.

## 2. Review of the literature

There is an ongoing debate regarding the existence of a causal relationship and the direction of the effect of oil prices on main macroeconomic aggregates (economic growth, exchange rate, inflation). Notably, the intensity of the oil price–macroeconomy nexus is related to a country's level of oil dependency, economic performance, economy status (oil-importing or oil-exporting), tax structure and the energy policy.

As a result, the findings of related empirical studies vary across countries (developed, developing, emerging, oil-importing, oil-exporting), model specifications, time periods, data frequency and econometric techniques employed in the analysis. However, the vast number of studies has focused on binary nexuses, i.e. either oil price and economic growth or oil prices and exchange rate or oil price and inflation (e.g., Bayat et al., 2015; Cunado & Pérez de Gracia, 2003; Lardic & Mignon, 2006), there is relatively less studies providing the analysis of all these variables (e.g., Ahmad et al., 2022; Basnet & Upadhyaya, 2015; Huang & Guo, 2007; Iwayemi & Fowowe, 2011; Ji et al., 2015), especially in the context of European countries.

Related empirical studies started by finding a negative linear relationship between oil prices and economic activity for advanced, oil-importing countries (Burbidge & Harrison, 1984; Darby, 1982; Gisser & Goodwin, 1986; Hamilton, 1983) utilizing the neoclassical theory in explaining this macroeconomic relationship. These starting findings spurred a vast number of researchers to a deeper consideration of the oil price-macroeconomy nexus based on various transmission mechanisms through which oil prices may affect the economic activity (e.g. channels of labor market, consumption, investment uncertainty, inflation, exchange rate) suggesting that the indirect transmission mechanism may be crucial in explaining oil price shocks on economy, i.e. and indirect influence of oil price changes on foreign exchange markets and inflation, beside the direct impact of oil prices on supply and demand (Beckmann et al., 2020; Bernanke et al., 1997; Ghalayini & Ghalayini, 2011; Lescaroux & Mignon, 2009; Shang & Hamori, 2024b).

However, since the mid-1980s, the effects of oil prices on economic activity estimated in the framework of linear models began to weaken its importance. Mork (1989) demonstrated for the U.S. economy that the effect of oil price increases is negative, and the effect of oil price decreases is positive but insignificant and substantially different from those of oil price increases. This evidence triggered a departure from the linear specifications assuming that oil prices rises and falls have symmetrically equal influence on the real economy. Besides asymmetric effects of oil price increases and decreases, other possible arguments for targeting non-linear models are mentioned e.g. significant structural breaks in most of the macroeconomic variables, the declining impact of oil on the economy and the role of monetary policy neutralizing the oil price shocks (Hooker, 1996; Hwang & Kim, 2024; Iwayemi & Fowowe, 2011; Shang & Hamori, 2024a).

Since this seminal work of Mork (1989), many authors have considered the possibility of the asymmetric effects of oil price changes on economic activity (Hamilton, 2003; Jiménez-Rodríguez & Sánchez, 2005; Lardic & Mignon, 2006, 2008; Mork et al., 1994; Moshiri, 2015) by applying the non-linear specifications (scaled specification, Lee et al., 1995; net specification, Hamilton, 1996) as the asymmetry is treated as a special case of non-linear relationship between oil prices and economic activity. The empirical findings are differentiated depending on the type of country, i.e. oil importing or exporting countries. For example, Jiménez-Rodríguez and Sánchez (2005), using two non-linear specifications in the framework of the VAR analysis for the G7 countries, Norway and the Euro zone as a whole, found that oil price rises have a significant negative impact on the GDP growth in all oil-importing countries except Japan, and declines in oil prices affect the GDP insignificantly for the most of countries (except US and UK). Whereas in Norway (oil-exporting country) oil price increases affected the GDP growth positively. Similarly, Cunado and Perez de Gracia (2003) found asymmetric effects of oil prices on economic activity when examining 14 European oil-importing countries within some non-linear specifications of the VAR models. Also, Lardic and Mignon (2006) who analysed 12 European countries (both oil importing and oil exporting) with the asymmetric cointegration approach concluded that an increase in oil prices influenced economic activity more than a decrease in oil prices. Some other authors have proposed the use of more advanced nonlinear econometric techniques to study the asymmetric impact of oil prices on economic activity. For example, authors who have used Markov-switching (MS) regime models include: Cologni and Manera (2009) for the G7 countries, Clements and Krolzig (2002) for the U.S. economy, Holmes and Wang (2003) for the U.K.; either Huang et al. (2005) who applied the multivariate threshold model for Canada, Japan and U.S.

The empirical analysis of asymmetric effects of oil prices on macroeconomic aggregates in the framework of non-linear models in the time domain is a common approach, however there is an alternative approach to capture non-linearity, namely examining this relationship in the frequency domain. Dependence across various frequency components (at the low frequencies corresponding to slowly fluctuating components, business cycle frequencies, and high frequencies corresponding to quickly fluctuating components) indicates the non-linearity of relationship (Ashley & Verbrugge, 2009; Shang & Hamori, 2024a; Zhu et al., 2023).

Studies on the oil price–economic activity nexus that have applied frequency domain causality are limited; nevertheless, some research can be included in this strand (Bayat et al., 2015; Gronwald, 2009; Kırca et al., 2020; Olayungbo, 2019; Wei, 2013; Wei & Guo, 2016). However, unlike our study, the existing studies have focused on pairwise relationships between oil (gas) prices and macroeconomic variables without considering differences in the causal patterns of different frequency components and without comparing them with the total pattern of causality in the time domain. In this way, our approach to examining causality in the frequency domain produces a more in-depth understanding of the relationship between oil (gas) prices and economic performance than analyses only in the time domain, as well provides crucial insights for a nation's economic policy and decision makers.

The empirical results in studies using the frequency domain causality differ based on a country status (oil importing or oil exporting) as well as a country's economic growth and energy policy and across frequencies and different types of variables; however, some common features can be distinguished. For instance, oil prices affected the economic growth (output, GDP, and industrial production) in Japan, Turkey, and China at low and/or business cycle frequencies (i.e., slowly fluctuating components) (Kırca et al., 2020; Wei, 2013; Wei & Guo, 2016), while no significant causal relationship was found between oil prices and industrial production in Germany (Gronwald, 2009). A causal relationship between oil price fluctuations and real exchange rates in the long run (low frequencies) has been found in Poland and the Czech Republic but not in Hungary and Nigeria, despite these economies being highly dependent on imported energy (Bayat et al., 2015; Olayungbo, 2019). The causal effects of oil prices on reserve in Nigeria (Olayungbo, 2019), export in China (Wei & Guo, 2016), stock market variables and short-term interest rates in Germany (Gronwald, 2009) have been found at high frequencies (at quickly fluctuating components). Notably, the causal effects of oil prices on the consumer price index (CPI) in Japan were significant at low frequencies, while in Germany they were significant at high frequencies.

All aforementioned studies have examined the oil price-macroeconomy nexus applying the traditional econometric techniques (like Granger causality followed by the vector autoregressive models (VAR) or vector error corrections models, VECM, or more advanced techniques like the Markov-switching regime models and multivariate threshold models) in the time domain and have represented similar approach in providing the stationarity of series and then explaining the cyclical movements of macroeconomic variables around long-run trends. Most widely the differencing technique and the Hodrick-Prescott (HP) filter are used to transform a non-stationary series into a stationary one. The former is more popular in academic work, and the latter in applied macroeconomic work by economists in central banks. However, the HP filter has been subject over many years to considerable criticism (Hamilton, 2018; Phillips & Jin, 2021) concerning its inadequacy for completely removing stochastic trends in macroeconomic time series and introduction of spurious dynamic relations. Therefore, in this study we apply the recently developed the boosted HP (bHP) filter which is more effective in trend fitting and trend elimination (Phillips & Shi, 2021), as well is free of the drawbacks of the HP filter. So far, this study is the first to apply the bHP filter to remove trend and examine the cyclical movements of the oil and gas price–macroeconomy nexus separately across different frequencies.

## 3. Econometric methods for time and frequency domain

### 3.1. The boosted Hodrick-Prescott filter

While many economists in international finance institutions, central banks, and government department use time series filtering methods extensively, one of the most popular trend extraction methods is the HP method because the HP filter has an extremely wide range of practical applications. However, this filter is less commonly used for scientific purposes, due to a series of numerical limitations, which studies have discussed (Cogley & Nason, 1995; Hamilton, 2018; Phillips & Jin, 2021; Phillips & Shi, 2021).

Researchers have largely discredited the HP filter, primarily emphasizing the demerits of the filter and why it should not be used. Only in recent years have researchers proposed approaches for improving the HP filter, increasing the power of testing, and reducing the generation of spurious relations and ways in which it could be used. Phillips and Shi (2021) provided an in-depth overview of the HP method and described a boosting algorithm for HP method.

The HP filter separates the time series ($x_t$) into two additive components, a trend component ($f_t$) and a cyclical component ($c_t$). The trend component is determined by solving the optimization problem as follows (Phillips & Shi, 2021):

$$\left(\hat{f}_t^{HP}\right) = \underset{(f_t)}{\arg\min} \left\{ \sum_{t=1}^{n} \left(x_t - f_t\right)^2 + \lambda \sum_{t=2}^{n} \left(\Delta^2 f_t\right)^2 \right\}; \quad (1)$$

$$\left(\hat{c}_t^{HP}\right) = \left(x_t - \hat{f}_t^{HP}\right), \quad (2)$$

where, $\Delta f_t = f_t - f_{t-1}$, $\Delta^2 f_t = \Delta f_t - \Delta f_{t-1} = f_t - 2f_{t-1} + f_{t-2}$, and $\lambda \geq 0$, is a tuning parameter that controls the extent of the penalty. Since the HP method is nonparametric, the choice of $\lambda$ parameter has a major role in determining the shape of the fitted trend and cycle components. For quarterly data, the standard choice is $\lambda = 1600$, as recommended by Hodrick and Prescott (1997) based on their experiment with US data.

We next detail an abbreviated description of the boosting algorithm for the HP method. The optimization problem (1) leading to the HP filter and related criteria for general filters of this type have closed-form algebraic solutions in convenient matrix form. In the case of the HP filter, the explicit form of the trend solution is (Phillips & Shi, 2021):

$$\hat{f}^{HP} = Sx, \quad (3)$$

where $S = \left(I_n + \lambda DD'\right)^{-1}$ is a deterministic operator, $x = \left(x_1, \ldots, x_n\right)'$ is the sample data, and $D$ is the rectangular $(n-2)\times n$ matrix with second differencing vector $d^{\,j}$ (1,−2, 1) along the leading tridiagonal and $I_n$ is the $n\times n$ identity matrix.

The smoothed component $\hat{f}^{HP}$ is interpreted as the estimated trend, then the estimated cyclical component $\left(\hat{c}^{HP}\right)$, which should be stationary takes the following form:

$$\hat{c}^{HP} = x - \hat{f}^{HP} = \left(I_n - S\right)x. \quad (4)$$

If the cyclical component $\hat{c}_t^{HP}$ still exhibits trending behavior after the HP filtering, continued use of the HP filter to $\hat{c}_t^{HP}$ to remove the leftover trend residual is recommended (Phillips & Shi, 2021). After a second fitting, the cyclical component can be written as follows:

$$\hat{c}^{(2)} = \left(I_n - S\right)\hat{c}^{HP} = \left(I_n - S\right)^2 x, \quad (5)$$

where the superscript 2 indicates that the HP filter is fitted twice. The corresponding trend component is now presented as follows:

$$\hat{f}^{(2)} = x - \hat{c}^{(2)} = \left(I_n - \left(I_n - S\right)^2\right)x. \quad (6)$$

If $\hat{c}^{(2)}$ continues to exhibit trend behavior, the filtering process may be continued for a third or further time. After $m$ repeated applications of the filter, the cyclical and trend component are:

$$\hat{c}^{(m)} = \left(I_n - S\right)\hat{c}^{(m-1)} = \left(I_n - S\right)^m x; \quad (7)$$

$$\hat{f}^{(m)} = x - \hat{c}^{(m)} = B_m x. \quad (8)$$

where $B_m = I_n - \left(I_n - S\right)^m$. This iterated process represents the bHP filter, and allows to establishment of a consistent estimation of stochastic process and deterministic trends in the data (Phillips & Shi, 2021; Shi, 2022).

### 3.2. Time domain analysis

Granger (1969) causality in the time domain is formulated for a wide-sen2.3se stationary time series. This concept is commonly used to analyze relationships between economic variables. The $p$-order vector autoregressive model (VAR($p$)) is estimated to investigate linear Granger causality (Granger, 1969):

$$\Theta(L)z_t = \varepsilon_t, \tag{9}$$

where, $z_t = [x_t, y_t]'$ and $\Theta(L) = I - \Theta_1 L - \ldots - \Theta_p L^p$.

Vector moving average representation of the VAR($p$) model takes the following form:

$$z_t = \Phi(L)\varepsilon_t = \begin{bmatrix} \phi_{11}(L) & \phi_{12}(L) \\ \phi_{21}(L) & \phi_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}, \tag{10}$$

where, the forecast variance of $x_{t+1}$ conditional on $X_t$ is denoted by $\sigma^2(x_{t+1}|X_t)$, and forecast variance is calculated with additional information about $Y_t$ and takes the form $\sigma^2(x_{t+1}|X_t \cup Y_t)$. The above allows for formulating that the variable $y_t$ is the Granger cause for $x_t$ if (Granger, 1969):

$$\sigma^2(x_{t+1}|X_t) > \sigma^2(x_{t+1}|X_t \cup Y_t). \tag{11}$$

The Hypothesis that $y_t$ does not cause $x_t$ in the time domain implies a linear restriction for the coefficients in the regression Equation:

$$x_t = \alpha_1 x_{t-1} + \ldots + \alpha_p x_{t-p} + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + u_t. \tag{12}$$

In linear Granger causality analysis, constraints in the form of Wald's zero restrictions are imposed on the lagged coefficients obtained from the VAR model estimation. We can find the causal relations between variables based on a Wald-type test; however, a causal test in the time domain yields only a single statistic for the entire sample, which is unsuitable for distinguishing causal relationships in the short-term, business cycle, and long-term. This means the Granger causality test in the time domain measures the precedence and information content in the variables (Joseph et al., 2015). Clive and Lin (1995) noted that the relationships between variables can differ in the sense of frequency bands, which are related to cyclical components. To obtain a more precise representation of the short-term, business cycle, and long-term causality mechanisms between variables, an analysis of Granger causality in the frequency domain should be performed. This approach is unconventional in the study of causality relative to studies in the time domain.

### 3.3. Frequency domain analysis

The framework developed by Breitung and Candelon (2006) is used to test Granger causality in the frequency domain. This method allows testing for the causality between economic variables at prespecified frequencies by applying the Choleski decomposition to the VAR representation expressed in Equation (9). If the system of variables is assumed to be stationary, the orthogonalized moving average (MA) representation can be derived as follows (Breitung & Candelon, 2006):

$$z_t = \Phi(L)G\eta_t = \Psi(L)\eta_t = \begin{bmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{bmatrix} \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix}, \quad (13)$$

where, $\Phi(L) = \Theta(L)^{-1}$ and $\Psi(L) = \Phi(L)G^{-1}$.

Based on the MA representation in Equation (13), the spectral density of $x_t$ can be written as follows:

$$f_x(\omega) = \frac{1}{2\pi}\left\{\left|\Psi_{11}\left(e^{-i\omega}\right)\right|^2 + \left|\Psi_{12}\left(e^{-i\omega}\right)\right|^2\right\}. \quad (14)$$

The null Hypothesis that $y_t$ does not cause $x_t$ at frequency ω takes the form (Breitung & Candelon, 2006):

$$H_0 : M_{y\to x}(\omega) = R(\omega)\beta = 0, \quad (15)$$

where, $\beta = \left[\beta_1,\ldots,\beta_p\right]'$ and $R(\omega) = \begin{bmatrix} \cos(\omega) & \cos(2\omega) & \ldots & \cos(p\omega) \\ \sin(\omega) & \sin(2\omega) & \ldots & \sin(p\omega) \end{bmatrix}$. Based on the measure of Granger causality suggested by Geweke (1982) and Hosoya (1991), Breitung and Candelon (2006) constructed a test for causality in the frequency ω by considering the null Hypothesis expressed in Equation (15). The test statistic takes the following form:

$$M_{y\to x}(\omega) = \frac{\left|\Psi_{12}\left(e^{-i\omega}\right)\right|^2}{2\pi f_u(\omega)}. \quad (16)$$

If the expression $\left|\Psi_{12}\left(e^{-i\omega}\right)\right| = 0$, then the statistic $M_{y\to x}(\omega)$ at frequency ω is equal to 0 ($M_{y\to x}(\omega) = 0$), indicating that there is no causality between the variables at a particular frequency. In the category of MA representation, $\left|\Psi_{12}\left(e^{-i\omega}\right)\right| = 0$ is equivalent to $\left|\Theta_{12}\left(e^{-i\omega}\right)\right| = \left|\sum_{k=1}^{p}\Theta_{12,k}\cos(k\omega) - \sum_{k=1}^{p}\Theta_{12,k}\sin(k\omega)i\right| = 0$, where $\Theta_{12,k}$ is (1,2)-element of $\Theta_k$ (Eq. (13)). This means the Breitung and Candelon (2006) approach is based on the linear restriction imposed on $\sum_{k=1}^{p}\Theta_{12,k}\cos(k\omega) = 0$ and $\sum_{k=1}^{p}\Theta_{12,k}\sin(k\omega) = 0$.

The test statistic for causality in the frequency domain (Eq. (16)) has the standard $F$ distribution as $F(2, T-2p)$. As with the conventional causality test, the test statistics are compared with the 5% critical value of the $F$ distribution to evaluate the significance of the Granger causality relationships between the variables in the frequency domain.

The causality measure in the frequency domain is extended to higher-dimensional VAR systems. Assume a three-dimensional VAR representation for stationary processes with the following form:

$$\begin{bmatrix} \Delta y_t \\ \Delta x_t \\ \Delta z_t \end{bmatrix} = \begin{bmatrix} \Psi_{11}(L) & \Psi_{12}(L) & \Psi_{13}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) & \Psi_{23}(L) \\ \Psi_{31}(L) & \Psi_{32}(L) & \Psi_{33}(L) \end{bmatrix} * \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \\ \eta_{3t} \end{bmatrix}. \quad (17)$$

Measuring the causal effect of $\Delta y_t$ on $\Delta x_t$ in a three-dimensional VAR system with $y_t = \left[\Delta y_t, \Delta x_t, \Delta z_t\right]'$ is related to bivariate causality measure after "conditioning out" the third variable ($\Delta z_t$) (Hosoya, 2001). Let $w_t$ denote the projection residual from a projection of $\Delta z_t$ onto the Hilbert space $H(\Delta y_t, \Delta x_t, y_{t-1}, y_{t-2}, \ldots)$. Furthermore, the residual projection from a projection of $\Delta y_t\left(\Delta x_t\right)$ on $H\left(w_t, w_{t-1}, \ldots\right)$ is $u_t\left(\upsilon_t\right)$, where $u_t = \Psi_{11}\left(L\right)\eta_{1t} + \Psi_{12}\left(L\right)\eta_{2t}$ and $\upsilon_t = \Psi_{21}\left(L\right)\eta_{1t} + \Psi_{22}\left(L\right)\eta_{2t}$. The causality measure is equivalent to the bivariate causality measure between $u_t$ and $\upsilon_t$ with form (Breitung & Candelon, 2006):

$$M_{\Delta y_t \to \Delta x_t | \Delta z_t}\left(\omega\right) \equiv M_{u \to \upsilon}\left(\omega\right). \tag{18}$$

Therefore, in higher-dimensional VAR system, the causality measure can be written as a bivariate causality measure with appropriately transformed variables.

## 4. Empirical analysis of relationships between fuel prices and economic activity in selected oil-importing and oil-exporting economies

The liquid fuel prices–economic activity nexus is next examined according to Figure 1, which includes six stages of research:

- *Stage 1*: The decomposition of macroeconomic variables into trend and cyclical components using the bHP filter (Phillips & Shi, 2021);
- *Stage 2*: Testing for the stationarity of bHP-detrended components across the given countries based on the Augmented Dickey–Fuller (ADF) test;
- *Stage 3*: Building the VAR models for the analyzed economies that form the basis for Granger causality testing;
- *Stage 4*: Testing for Granger causality in the time domain based on the Wald test;
- *Stage 5*: Testing for Granger causality in the frequency domain based on the Breitung–Candelon test;
- *Stage 6*: Robustness check using cross-spectral analysis (coherence coefficient).

We apply a commonly used framework in macroeconomics, the Aggregate Demand, Aggregate Supply (AD/AS) model (Chiarella et al., 2006; Dutt & Skott, 2006) to justify the determinants of macroeconomic fluctuations and the performance of key macroeconomic variables. When selecting variables for a VAR model based on the AD/AS model, it is essential to consider the variables that are most relevant for capturing the dynamics of aggregate supply and demand in the economy. As this study is considered in the context of the effect of changes in two major fuel prices of oil and gas, the key variables in the VAR model include Brent oil prices (OIL–$ per barrel), global gas prices (GAS–$ per million metric British thermal units), GDP–index: 2015 = 100), inflation (CPI–index: 2015 = 100) and the exchange rate (ExR–national currency per $ rate). The data collected for this research comes from the FRED database (https://fred.stlouisfed.org/). Besides oil (and gas) prices and GDP, the remaining variables selected for the study (inflation and exchange rate) are included to represent some of the most important transmission channels through which oil (and gas) prices may affect economic activity indirectly through inflation and exchange rate, i.e. price level (represented by inflation rate) reflects changes in aggregate supply, and the exchange rate is important in open economies as it affects the international trade and capital flow, with implications for aggregate demand and supply.

As previously noted, the relationship between liquid fuel prices and economic activity is investigated for three selected economies, including Germany, Poland (representing net oil

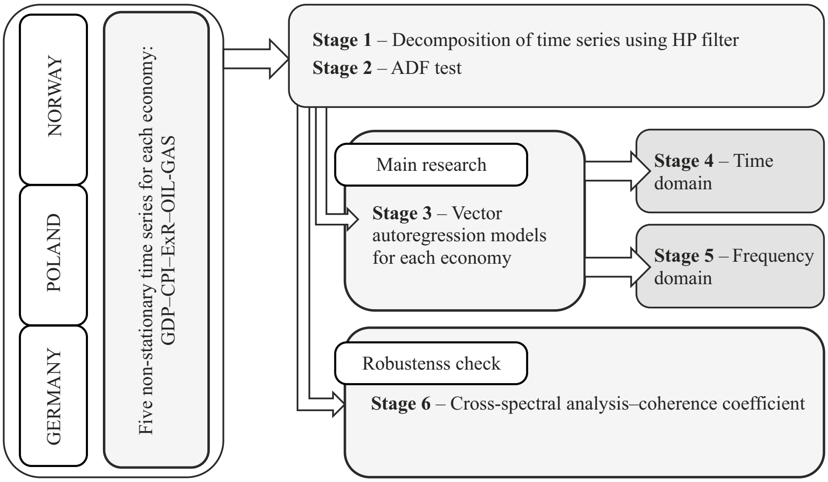



**Figure 1.** The study design of the Granger causality for oil-exporting and oil-importing economies in the time and frequency domain

importing economies), and Norway (representing a net oil exporting economy). The choice of these economies for the study was made to reflect different energy dependence, diverse economic structures, near geographic location between economies and energy policy responses. Germany is one of the largest energy consumers in Europe, is heavily reliant on imported oil and gas, and is a highly economically developed country with a minimal proportion of coal in the energy mix. Although Poland is also reliant on imported oil and gas, its energy generation is heavily dependent on the burning of coal, with over 70% of power generated by coal. This makes the Polish economy in need of accelerated transition to a low-carbon economy. Norway is a major producer and exporter of oil and gas, with a dominant share of oil and gas in its energy mix. Oil and gas is Norway's largest sector based on value added, investments, and export value (IEA, 2022). As such, this sector has a crucial influence in the Norwegian economy and in financing the Norwegian welfare state. As a result, the nation's entire economy is highly dependent on oil and gas prices. To mitigate the impact of fuel price volatility and stabilize the economy, Norway has established a sovereign wealth fund, called the Government Pension Fund Global (Det Kongelige Finansdepartement, 2020). These three countries differ in terms of energy policies. Poland has been implementing energy diversification policies to reduce dependence on coal and oil, while Germany has been transitioning toward renewable energy sources as part of its Energiewende policy (Jacobs, 2012). In Norway, energy technology and innovation have a crucial role in the nation's energy transition; in particular, leveraging the existing strengths of its energy sector in hydrogen, offshore wind, a future-oriented oil–gas industry with low emissions from upstream activities, and carbon capture and storage (IEA, 2022). Analyzing the complex relationships between oil and gas prices and economic activity in these countries can provide valuable insights and help policymakers and researchers understand the implications of oil price fluctuations on the different types of economies more comprehensively.

### 4.1. Stages 1 and 2. Decomposition of variables and ADF test for detrended components

All variables must be detrended prior to constructing the VAR model. The application of a differential filter is a straightforward and commonly used method as it removes a unit root component from the time series. While this filter eliminates a wide band of low frequencies (long-term fluctuations), it also distorts the high-frequency band (Estrella, 2007). As a consequence, this may affect the causal links revealed between the variables transformed by this filter. The second most commonly used filter is the HP filter. As studies have indicated (Hamilton, 2018), the HP filter has significant disadvantages, including spurious cycles, bias at the sample end, and ad hoc hypotheses for smoothing parameters. As previously described, we apply the bHP filter (a modified HP filter), which extracts the stochastic trend (unit root) by passing the low-frequency band and removing the high-frequency band to avoid these issues. The stationary cyclical components for each variable are obtained by subtracting the bHP-filtered series from the original series. The results in Table 1 confirms that all variables transformed in this manner are stationary.

**Table 1.** ADF test for the bHP-detrended component for the selected economies

| Market / Economy | Variable | Levels | Decision |
|---|---|---|---|
| *Fuel prices* | $OIL_t$ | –6.485 (c) *** | I(0) |
| | $GAS_t$ | –7.07 (c) *** | I(0) |
| *Germany* | $GDP_t$ | –7.132 (c) *** | I(0) |
| | $CPI_t$ | –7.468 (c) *** | I(0) |
| | $ExR_t$ | –7.214 (c) *** | I(0) |
| *Poland* | $GDP_t$ | –6.836 (c) *** | I(0) |
| | $CPI_t$ | –7.143 (c) ** | I(0) |
| | $ExR_t$ | –7.164 (c) *** | I(0) |
| *Norway* | $GDP_t$ | –7.439 (c) *** | I(0) |
| | $CPI_t$ | –6.192 (c) *** | I(0) |
| | $ExR_t$ | –6.862 (c) *** | I(0) |

*Note*: ** and *** denote significance at 5% and 1% levels, respectively.

### 4.2. Stage 3. Vector autoregressive model (VAR)

Based on the cyclical components of the variables, the VAR model is constructed to examine the relationship between fuel prices (oil and gas prices) and fundamental macroeconomic variables describing economic performance across the selected economies and to test for causality in time domain and frequency domain (long-term, business cycle, and short-term components).

The five-dimensional vector autoregression model (VAR) takes the following form:

$$Y_t = A_0 + \Gamma_i D_t + \sum_{i=1}^{P} A_i Y_{t-P} + E_t, \tag{19}$$

where, $Y_t = \left[GDP_t, CPI_t, ExR_t, OIL_t, GAS_t\right]$ is a vector of the stationary cyclical components of a given variable determined in Stage 2; $A_0$ is a vector of the intercept terms; $A_i$ denotes the coefficient matrices, which reflect the short-term dynamic relationship between the variables; $E_t$ is a vector of the disturbance terms, and $D_t$ is a vector of the dummy variables that describes outliers (e.g., d_03–dot-com crisis, d_08-financial crisis in 2008–2009, d_14-oil price drop out in 2014–2015, d_20-COVID-19 epidemic outbreak in 2020). The dummy variables are found to be significant for all analyzed economies. The lag order ($p$) for the VAR model for each economy is identified using the Akaike information criterion ($p$ = 3 for Germany, $p$ = 6 for Poland, and $p$ = 4 for Norway).

We also test the reliability of the VAR models by applying autocorrelation and normality diagnostics tests. The LM test for fourth order residual autocorrelation is not significant, but normality is clearly violated in the VAR models for Germany and Poland (Table 2); however, this lack of normality is due to excess kurtosis, which is not as serious for the estimation results as a lack of symmetry in the residual distribution (Juselius & MacDonald, 2000). Notably, the latter is not violated in any VAR models.

**Table 2.** Residual diagnostics (autocorrelation, heteroskedasticity, and normality tests)

| Tests | Net-oil importer: Germany | | | | |
|---|---|---|---|---|---|
| | $GDP_t$ | $CPI_t$ | $ExR_t$ | $OIL_t$ | $GAS_t$ |
| Chi-sq ($\chi^2$) | 921.255 ($p$ = 0.575) | | | | |
| LM test (lag = 4) | 1.317 ($p$ = 0.151) | | | | |
| Joint JB test | 14.769 ($p$ = 0.141) | | | | |
| JB | 4.878 | 4.878 | 4.878 | 4.878 | 4.878 |
| Skewness | 0.192 | 0.192 | 0.192 | 0.192 | 0.192 |
| Kurtosis | 4.006** | 4.006** | 4.006** | 4.006** | 4.006** |
| Tests | Net oil importer: Poland | | | | |
| | $GDP_t$ | $GDP_t$ | $GDP_t$ | $GDP_t$ | $GDP_t$ |
| Chi-sq ($\chi^2$) | 986.619 ($p$ = 0.391) | | | | |
| LM test (lag = 4) | 1.290 ($p$ = 0.169) | | | | |
| Joint JB test | 17.83 ($p$ = 0.058) | | | | |
| JB | 1.078 | 1.078 | 1.078 | 1.078 | 1.078 |
| Skewness | 0.24 | 0.24 | 0.24 | 0.24 | 0.24 |
| Kurtosis | 2.839 | 2.839 | 2.839 | 2.839 | 2.839 |
| Tests | Net oil importer: Norway | | | | |
| | $GDP_t$ | $GDP_t$ | $GDP_t$ | $GDP_t$ | $GDP_t$ |
| Chi-sq ($\chi^2$) | 511.029 ($p$ = 0.2997) | | | | |
| LM test (lag = 4) | 1.0029 ($p$ = 0.4631) | | | | |
| Joint JB test | 17.127 ($p$ = 0.072) | | | | |
| JB | 4.853 | 4.853 | 4.853 | 4.853 | 4.853 |
| Skewness | 0.248 | 0.248 | 0.248 | 0.248 | 0.248 |
| Kurtosis | 3.934 | 3.934 | 3.934 | 3.934 | 3.934 |

*Note*: ** and *** denote significance at 5% and 1% significance levels, respectively.

### 4.3. Stage 4–5. Granger causality analysis in time domain and frequency domain

The VAR models describing the relationship between oil (gas) prices and macroeconomic variables (GDP, CPI, and ExR) for Germany, Poland, and Norway constitute the basis for the Granger causality testing in the time domain (Table 3). The frequency domain causality tests are performed to examine the causal mechanism between the variables in question for the three selected economies (Figure 2, Figure 3).

Figure 2a–f report the p-values of the causality measures (Breitung–Candelon statistics) between liquid fuel (oil and gas) prices and other variables for different cycle lengths $(2\pi / \omega)$ corresponding to all frequencies $\omega \in (0,\pi)$ together with the 5% and 10% significance level for the three selected countries (the other results of the frequency causality measures from other variables to liquid fuel price are presented in Appendix Figure A1). The full results of the causality tests are presented in the form of causal patterns for each frequency components combined with the total time domain causal pattern (Figure 3). We focus on three components in interpreting these results: (1) a long-term component within a frequency band (0.059; 0.117) corresponding to periods between 26.7 years (107 quarters) and 13.37 years (54 quarters); (2) a business cycle component with a frequency band (0.117; 0.763) corresponding to periods between 13.37 years and 2.01 years; and (3) short-term component with a frequency band from 0.76 to 3.11, corresponding to periods shorter than two years (Appendix Table A1).

**Table 3.** Results of Granger causality in the time domain (Wald test statistics based on VAR model)

| Dependent variables | Explanatory variables | | | | |
|---|---|---|---|---|---|
| | Net oil importer | | | | |
| | Germany | | | | |
| | $GDP_t$ | $CPI_t$ | $ExR_t$ | $OIL_t$ | $GAS_t$ |
| $GDP_t$ | – | 34.685*** | 8.032 | 9.169 | 11.541* |
| $CPI_t$ | 10.882* | – | 5.248 | 2.104 | 12.51* |
| $ExR_t$ | 4.926 | 11.696* | – | 12.71** | 7.047 |
| $OIL_t$ | 3.577 | 19.145*** | 12.632*** | – | 26.87*** |
| $GAS_t$ | 6.233 | 16.865*** | 12.399* | 20.59*** | – |
| Poland | | | | | |
| | $GDP_t$ | $CPI_t$ | $ExR_t$ | $OIL_t$ | $GAS_t$ |
| $GDP_t$ | – | 2.771 | 3.732 | 3.477 | 1.795 |
| $CPI_t$ | 16.86*** | – | 8.93 | 2.298 | 9.548 |
| $ExR_t$ | 2.611 | 7.311 | – | 12.167* | 2.015 |
| $OIL_t$ | 3.645 | 5.957 | 5.595 | – | 21.238*** |
| $GAS_t$ | 2.292 | 9.275 | 8.964 | 15.244** | – |
| Net oil exporter | | | | | |
| Norway | | | | | |
| | $GDP_t$ | $CPI_t$ | $ExR_t$ | $OIL_t$ | $GAS_t$ |
| $GDP_t$ | – | 18.168*** | 14.200*** | 4.132 | 3.698 |
| $CPI_t$ | 13.309*** | – | 3.272 | 4.791 | 5.889 |
| $ExR_t$ | 0.266 | 14.297*** | – | 3.940 | 1.989 |
| $OIL_t$ | 13.475*** | 8.794*** | 5.989 | – | 17.68*** |
| $GAS_t$ | 2.434 | 13.572*** | 3.619 | 2.255 | – |

*Note*: *, **, and *** denote rejection of the null hypothesis (no Granger causality) at 10%, 5%, and 1% significance levels, respectively.

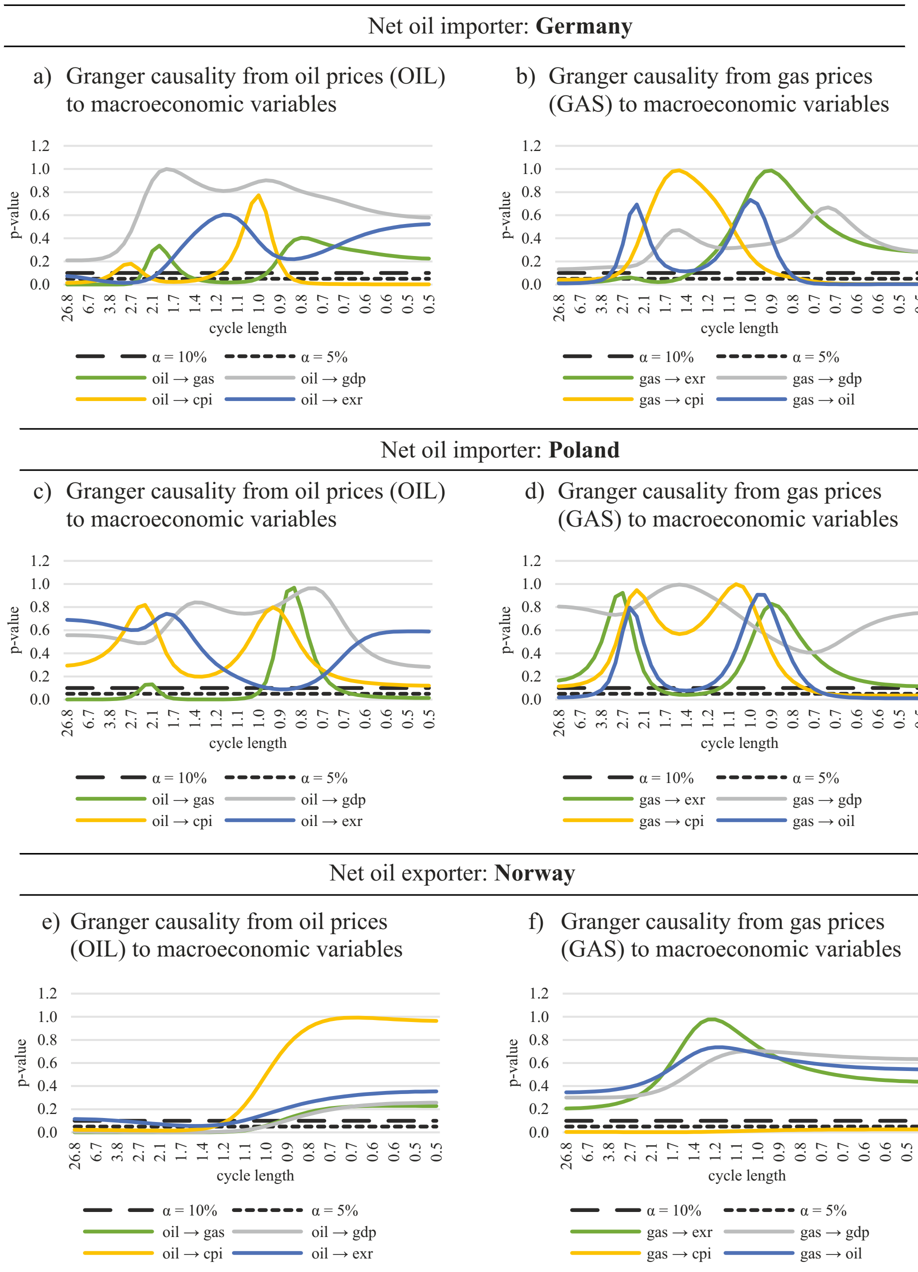



**Figure 2.** Frequency domain causality test results (p-values for Breitung-Candelon test)

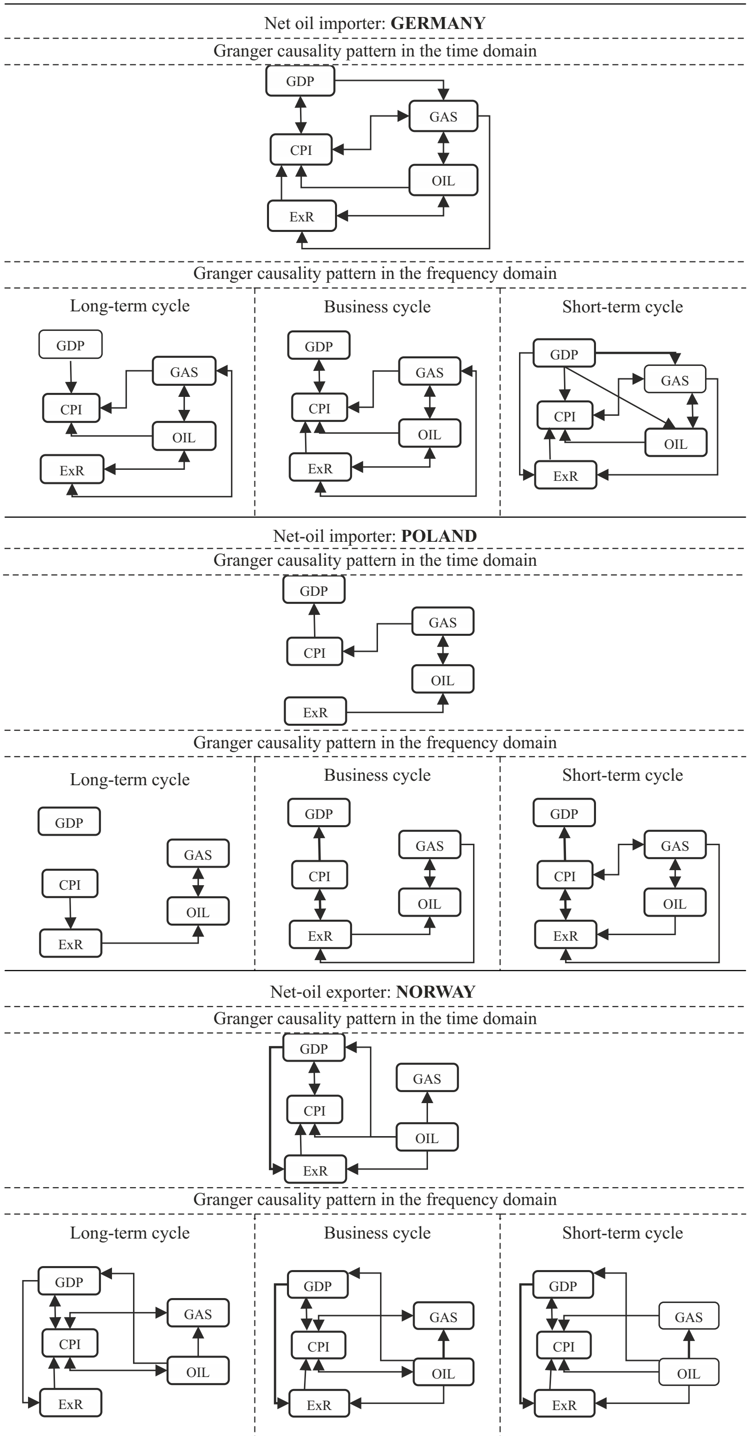



**Figure 3.** Granger causality between liquid fuel prices and macroeconomic variables in the time domain and frequency domain

In the case of Germany (Figure 2a), the results reveal that oil prices affect the CPI, exchange rate (ExR), and gas prices (GAS) in the business cycle and long-term cycle, within the frequency band of 0.059 to 0.763, corresponding to periods between 26.7 and 2.01 years. Meanwhile, no Granger causality running from oil prices to GDP is evident for all frequencies. A significant impact of oil prices on CPI and gas is also found in Germany for a high-frequency band, revealing significant relationships for cycle length from 2.01 to 1.2 years for CPI and 2.01 to 0.9 years for GAS. In the case of Poland (Figure 2c), similar to Germany, the pattern of causal impact of oil prices on the macroeconomic variables differs. Significant causality running from oil prices to the ExR are evident for the short-term cycle components for frequencies between 1.762 and 1.938, which corresponds to cycle lengths between 0.9 and 0.8 years. Furthermore, oil prices affect gas prices at all frequencies, and CPI and GDP are not affected by oil prices for all frequencies.

Both oil-importing countries also differ in terms of the effect of gas prices on macroeconomic variables (Figure 2b and 2d). In Germany, the CPI is affected by gas prices for frequencies between 0.059 and 0.528 and 1.879–3.11, which corresponds to periods longer than 3 years and shorter than one year, while, in Poland, causality running from gas prices to the CPI is only found for high frequencies between 0.881 and 1.351, corresponding to cycle lengths between 1.8 and 1.2 years. In addition, causality from GAS to ExR is evident in both economies; however, in Poland, a significant impact of gas prices on the exchange rate is only evident for short-term components corresponding to cycle lengths between 2.0 and 1.1 years. In Germany, the relationship between GAS and ExR is evident for high frequencies above 1.115, which corresponds to cycles above 1.4 years. Notably, no causality is found running from GAS to GDP in either oil-importing country. Moreover, gas prices affect oil prices in Germany and Poland in a similar manner.

Regarding the oil-exporting country of Norway (Figure 2e–f), gas prices, GDP, and the CPI are affected by oil prices for almost all frequency bands. The exceptions are cycle lengths shorter than one year in OIL–GAS and OIL–GDP relationships and the OIL–CPI relationship for cycles shorter than 1.2 years (Figure 2e). A significant causal impact is revealed for oil prices on the Norwegian krone exchange rate for cycle lengths between 2.5 and 1.2 years. The impact of gas prices on macroeconomic variables in Norway is only evident in the case of CPI for all frequency bands; however, the remaining variables (OIL, ExR, and GDP) are not affected by gas prices (Figure 2f).

The description of the causality results in both time and frequency domains involves: (1) the identification of country-specific causality patterns and (2) the comparison of causal patterns in the frequency domain (representing a nonlinear approach) with those obtained in the time domain (representing a linear approach) for studied economies.

## 4.4. Oil-importing economy: Germany

The results presented in Figure 3 show that the patterns of causality at various frequencies in Germany differ slightly from the corresponding results in the time domain. In particular, an important interaction is evident between oil and gas prices for all frequencies and fuel prices and the exchange rate at low and business cycle frequencies. Moreover, a unidirectional relationship running from gas prices and the exchange rate is apparent at high frequencies corresponding to periods shorter than about two years. We also note that oil and gas prices cause CPI changes at frequencies below 0.763 corresponding to periods longer than two years (the long-term and business cycle causality patterns in Figure 3), while the interaction between gas prices and CPI is apparent in the short-term (at high frequencies above 0.763). The impact of oil and gas prices on GDP is indirectly observed for business cycle frequencies through CPI and ExR, and for high frequencies an opposite relationship direction appears (directly from GDP to fuel prices). The evident causality running from oil and gas prices to exchange rate and CPI for all frequencies (long-term, business, and short-term cycles) confirms that oil and gas price fluctuations are important for the German economy in which oil and gas are the predominant energy sources.

Comparing the findings of causality at various frequencies with those obtained in the time domain reveals that the pattern of causality between fuel prices (oil and gas), exchange rate, and CPI in the time domain is dominated by corresponding causality observed in long-term and business cycle frequencies, in addition to the short-term interaction between CPI and gas prices, and short-term impact of gas prices on GDP. This means that the predictive power of oil and gas prices for key macroeconomic variables occurs for slow and fast fluctuating components. This implies that policymakers should combine short-term corrective actions to stabilize the economy with long-term structural policy.

### 4.5. Oil-importing economy: Poland

Although the causal patterns at various frequencies in Poland differ from those of Germany, the key interactions between oil and gas prices are also present at all frequencies for the Polish economy (Figure 3: Poland). Moreover, oil and gas prices exhibit direct predictive power for the exchange rate and CPI at high frequencies (corresponding to periods shorter than two years) and indirect predictive power at business cycle frequencies. Notably, the indirect impact (through ExR and CPI) of fuel prices on GDP is found for business and short-term cycles, but not for the long-term cycle.

A comparison of causality results at various frequencies with those obtained in the time domain shows that the pattern of causality in the time domain is dominated by the short-term causality as the indirect impact of oil and gas prices on GDP is the most apparent, and the influence of exchange rate is evident for low and business cycle frequencies. These findings indicate that the predictive power of oil and gas prices for economic activity is concentrated at the quickly and slowly fluctuating components as in Germany; however, the causality patterns differ considerably. A possible explanation for this might be the countries' differences in economic structure, energy mix, and energy efficiency (oil and gas-intensive German economy and carbon-intensive Polish economy).

### 4.6. Oil-exporting economy: Norway

Since Norway is an oil-exporting economy, the causal patterns exhibit some differences to those obtained for two oil-importing economies; however, the findings demonstrate that oil and gas prices have predictive power for future changes in macroeconomic variables. Specifically, oil prices affect gas prices, GDP, and CPI for all frequencies. Moreover, an interaction is evident between oil prices and CPI, and gas prices and CPI for long-term and business cycles (corresponding to periods longer than five years). Additionally, for business and short-term cycles (periods below about five years), oil prices influence the exchange rate of the Norwegian krone. These findings indicate that slowly fluctuating components of oil and gas prices can predict the corresponding components of future GDP growth and changes in CPI, and the quickly fluctuating components of oil and gas prices can predict the corresponding components of exchange rate. The results demonstrate that the relationships between OIL–CPI, GAS–CPI, OIL–GDP, and OIL–ExR, have a pivotal role in transferring changes caused by disruptions in the oil market to economic activity. This is because the petroleum sector has a dominant role in Norway's economy and financing the Norwegian welfare state. Revenue from sales of oil and gas are essential for the stability of the state budget and have a significant supportive function in the modern Norwegian society (Det Kongelige Finansdepartement, 2020).

Comparing frequency causality results with those existing in the time domain reveals that crucial dependencies between fuel prices (oil and gas) and fundamental macroeconomic variables at various frequencies are also apparent in the time domain, presenting impact of oil prices on GDP, gas prices, and CPI for the long-term cycle, and impact of oil prices on exchange rate for business cycle and short-term cycles. The results demonstrate that the predictive power of oil and gas prices is focused on both slowly and quickly fluctuating components which is of great relevance for macroeconomic policymakers, indicating that oil and gas prices may be used to improve predictions for slowly fluctuating components of the GDP growth and changes in CPI to initiate appropriate stabilizing actions in advance to better anticipate future economic activity. Furthermore, the fast-moving components of oil and gas prices can better predict the corresponding components of the exchange rate, and policy interventions are less critical in that case as these movements in oil and gas prices are temporary.

## 5. Robustness check

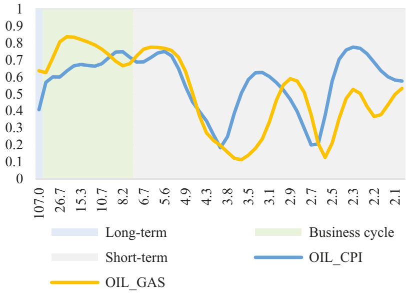
The robustness of the results on relationship between liquid fuel prices and economic activity is tested by applying a cross-spectral coherence coefficient. The coherence coefficient $\left(Coh_{\overrightarrow{xy}}(\omega)\right)$, along with spectral density ($f_x(\omega)$; $f_y(\omega)$) and cross-spectral density ($f_{xy}(\omega)$) functions, is among the basic spectral characteristics. The coherence coefficient for $X \Rightarrow Y$ and $X \Leftarrow Y$ takes the following form (Kijek, 2017):

$$Coh_{\overrightarrow{xy}}(\omega) = \frac{\left|f_{xy}(\omega)\right|}{\left[f_x(\omega) f_y(\omega)\right]^{0,5}}. \tag{20}$$

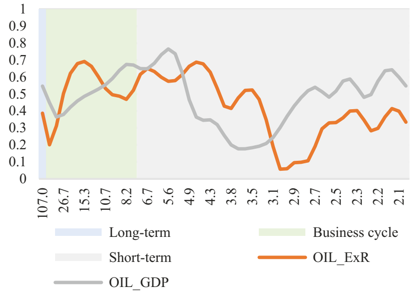
Coherence coefficients are analyzed for the same three frequency bands as the previous frequency causality analysis (see Appendix Table A1). The coherence coefficient is normalized in the interval [0, 1] and measures the strength of the linear relationships between corresponding frequency bands for all time lags and leads. Figure 4 illustrates the cross-spectral coherence among macroeconomic variables (GDP, CPI, and ExR) and liquid fuel prices (Oil, GAS) for Germany, Poland, and Norway.

PANEL A: Net oil importer: **Germany**

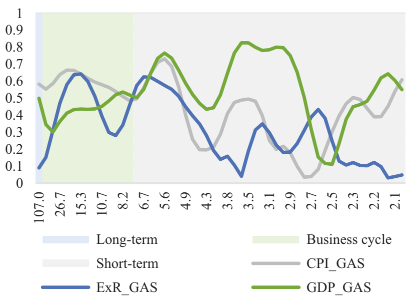
A.3.1



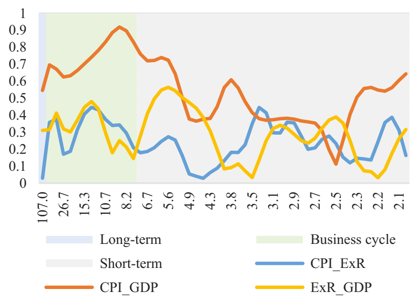

A.3.2




A.3.3

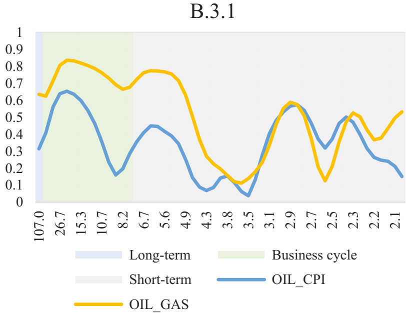



A.3.4

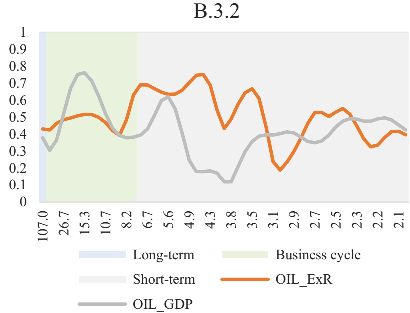



PANEL B: Net oil importer: **Poland**

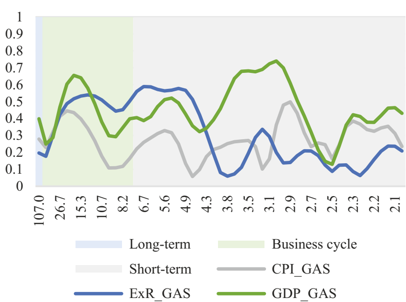
B.3.1




B.3.2




B.3.3




B.3.4

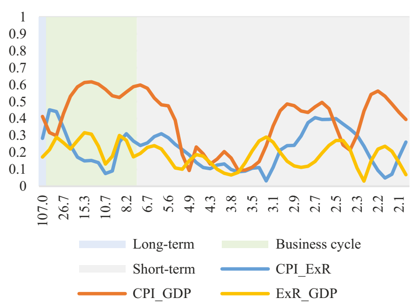



**Figure 4.** *Continued on next page*

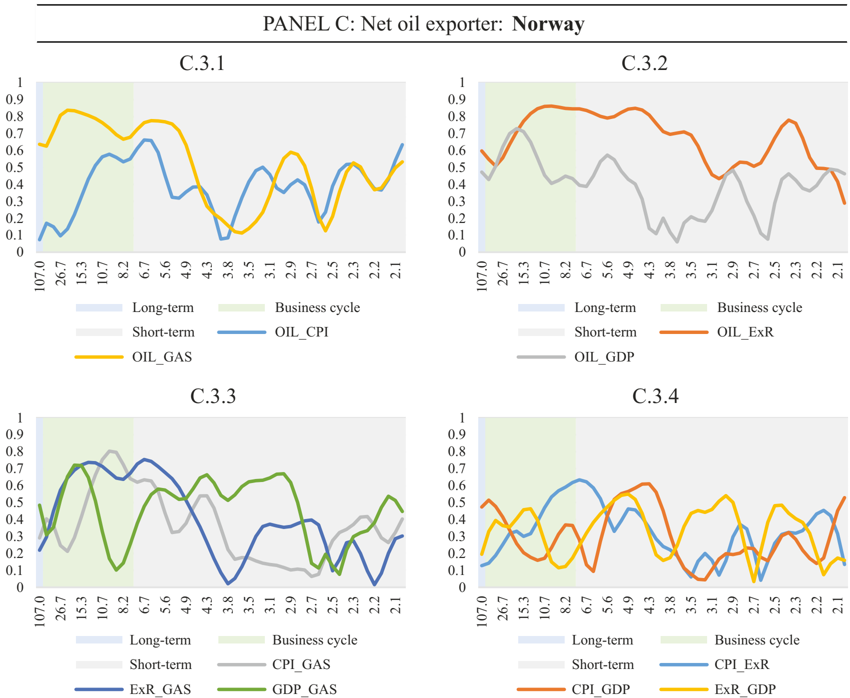



**Figure 4.** Coherence between series detrended with the bHP filter

Figure 4 shows the coherence coefficient between series detrended using the bHP filter, which reveals similar connections at various frequencies in comaprision to the results of the Breitung–Candelon causality test (Figure 3). For all countries, the coherence between OIL and GAS prices is high (from about 0.6 to 0.8) for all frequency bands (long-term, business cycle, and short-term), which confirms the causality results in the time and frequency domain that the links are bi-directional $(OIL \leftrightarrow GAS)$ for Germany and Poland and unidirectional $(OIL \rightarrow GAS)$ for Norway.

In the case of Germany, the interactions between liquid fuel prices (OIL and GAS) and CPI are strong (coherence about 0.6), with the highest coherence appearing in the business cycle (shorter than five years) and short-term cycles (below two years). The connections between fuel prices and CPI are slightly weaker for slowly fluctuating components (long-term cycle). That is also the case for Norway, but the interactions between liquid fuel prices (OIL and GAS) and CPI are noticeably weaker at slowly fluctuating components. In the case of Poland, the relation between OIL and CPI refers to all frequency bands, while the GAS–CPI relationship also occurs for all frequency bands, and the coherence coefficient demonstrates that this relation is stronger than the OIL–CPI relationship. The coherence between fuel prices and ExR indicates a stronger connection at rapidly fluctuating components in comparison to slowly fluctuating components, for Germany and Norway; however, this connection is visibly stronger for the Norwegian economy, especially for the OIL–ExR relationship. For Poland, the OIL–ExR and GAS–ExR connections are stronger for high frequencies (short-term components) than for low frequencies (long-term components). The coherence results also confirm causality running from liquid fuel prices (OIL and GAS) to CPI and ExR across the analyzed frequency bands.

Strong interactions are also evident between OIL–GDP and GAS–GDP for quickly fluctuating components for Germany, whereas this interaction is identified for Norway in all frequency bands at the moderate level of coherence. These findings align with our previous results from the Breitung–Candelon causality test showing the causality between fuel prices and GDP, although direct causality between fuel prices and GDP is only reported for Norway, and indirect causality through CPI for Germany and through GAS and CPI for Poland. This evidence supports the results of the Breitung–Candelon causality test, validating the robustness of our results.

## 6. Discussion and conclusions

The purpose of this study was to distinguish the long-term, business cycle, and short-term predictability of liquid fuel prices for macroeconomic variables for comparison with the causal relationships in the time domain for three selected European countries (Germany, Poland, and Norway). The empirical findings demonstrate that the causal patterns between liquid fuel price (oil and gas) changes and economic activity in the frequency domain exhibit some noticeable differences compared with those obtained in the time domain. The frequency domain causality analysis makes it is possible to identify which frequency components dominate the total time domain causality pattern. Moreover, marked differences in the patterns of causality between fuel prices and changes in economic activity are visible based on oil-importing (Germany, Poland) or oil-exporting (Norway) economic status. Notably, these findings would be undetectable by conventional causality tests in the time domain.

In Germany, the direct impact of oil and gas prices on CPI and ExR is apparent for all frequencies, and while the impact on GDP is indirectly observed through CPI and ExR for business cycle frequencies, the opposite direction of causality running directly from GDP to both oil and gas prices is observed for high frequencies (short-term components). These results indicate that the German economy is highly dependent on oil and gas. Although, fuel prices and fundamental macroeconomic variables are characterized by short- and long-term relationships, this does not mean that the short-term impact of fuel prices on macroeconomic variables is necessarily a suitable guide to this relationship in the long term. In the long term, the influence of fuel price shocks (increase of fuel prices) on the economy can change, along with changes in the structure of the economy and policy framework (e.g., continued gains in energy efficiency achieved in Germany over the past decades mitigated some of the negative effects of higher fuel prices). Comparing these findings of causality with the results of conventional causality tests (in the time domain), the crucial relationships between fuel prices and fundamental macroeconomic variables are also apparent in the time domain. This result underscores the importance of the long- and short-term relationships between fuel prices and macroeconomic variables, calling for short-term monetary interventions to stabilize inflation and the exchange rate and long-term structural policies, such as changes in the structure of economy, development and adoption of new technologies, and improvements in energy efficiency.

While Poland is an oil-importing country, a notably different pattern emerges for the relationship between the fuel prices and macroeconomic variables compared with Germany. Specifically, oil and gas prices directly affect ExR and CPI in the short-term cycle (periods shorter than two years) and indirectly in the business cycle (from two to 13 years.), while the indirect impact on GDP (through CPI and ExR) is revealed at business cycle and high frequencies but not at low frequencies (long-term cycle). The predictive power of oil and gas prices for CPI and GDP seems to dominate at faster fluctuating components as the short-term impact of fuel prices on CPI and GDP is also present in the time domain. Since short-term fuel price shocks are temporary, policymakers' corrective actions are less important. Nevertheless, some corrective actions to stabilize inflation and the exchange rate should be initiated to reduce the adverse effects of fuel shocks on consumers and households. At the medium-term frequencies relevant to the business cycle, demand is already more elastic and can adjust to higher fuel prices more easily due to oil substitution and conservation; for example, through the use of alternative and renewable energy sources and improvements in oil-use efficiency. Therefore, policymakers can design flexible regulations that are differentiated for short and medium terms.

A possible explanation for the differences in the causal patterns in the time and frequency domains in Poland and Germany may be differing levels of economic development and dependency on gas and oil import and also key differences in the energy mix (i.e., Poland still has a highly carbon-intensive economy due to the dominance of coal in its energy mix, whereas Germany's energy mix is dominated by oil and gas).

In Norway, the direct impact of oil and gas prices on GDP and CPI is evident for all frequencies, while the ExR is only directly affected by fuel prices at faster fluctuating components (short-term cycles). In the time domain, the unidirectional causality from oil prices to gas prices, CPI, GDP, and ExR occurs for short-term components; therefore, the relationships at rapidly fluctuating components seem to be of great relevance for the Norwegian economy. However, OIL–GDP–CPI and OIL–GDP–ExR–CPI causal relationships that are evident at slowly and fast fluctuating components make oil price fluctuations a crucial consideration for the short- and long-term. Therefore, policymakers can use oil and gas prices to significantly improve predictions for the slowly fluctuating components of GDP growth and changes in CPI and ExR, and formulate policies that anticipate the future economic activity more accurately. While the fast-moving components of oil and gas prices can better predict the corresponding components of CPI, exchange rate, and GDP, policy interventions are less critical in such cases as oil and gas price increases lead to a transfer of wealth from oil-importing countries through a shift in the terms of trade. Accordingly, policymakers should focus on coordinating long- and medium-term policies to prevent oil and gas prices from moving too far from a range of possible equilibrium prices, ensuring that the long-term the supply and demand are elastic, and higher oil and gas prices create incentives for developing and implementing oil-efficient technologies in oil-importing countries which will reduce oil demand.

This study demonstrates that although the effects of fuel price shocks on macroeconomic aggregates seem to be similar across countries, the causal patterns differ considerably due to varying economic structures, energy mix, and energy intensity, oil importing or exporting status, the development of alternative energy sources and fuels, and end-users' ability to reduce consumption of non-renewable energy sources and transition to renewable ones. As a result, the causal associations between fuel prices and macroeconomic factors must be examined in the specific context of a particular economy. Accordingly, policymakers should formulate policies that are differentiated to periods and oil importing or exporting status. As the volatility of fuel prices (especially increases) cause major business cycle variations and downturns in the oil-importing countries, providing information on causality patterns between fuel prices and macroeconomic aggregates from long-term, business cycle, and short-term perspectives will aid policymakers in aligning policies aimed at strengthening energy security (e.g., by advancing efforts to diversify the supply of fuels and energy and emphasizing the need to increase renewable energy supply. Oil price movement primarily affects revenue from energy export and government budget revenue in oil-exporting country. Therefore, knowing the predictive power of fuel prices for macroeconomic aggregates separately for slowly, business cycle, and fast fluctuating components can help policymakers prepare for episodes of large prices fluctuations based on changes in oil and gas supply and demand conditions.

Our results concerning the causal relationship between fuel prices and macroeconomic aggregates across different frequencies with the use of the Breitung-Candelon causality test have some limitations. Namely, this test is able to determine only the direction of causality but not to indicate the sign of causal relationships. Hence, in our further research we will apply the impulse response function to provide information on what sign is associated with the response of fundamental macroeconomic variables to the increases or decreases of fuel prices in both frequency and time domains.

## Acknowledgements

This work was conducted under research project No. FUTURE/03/2022 "Crude oil prices and economic activity nexus in selected European countries–analysis over the spectrum," received from the University Centre of Excellence.

## Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

## Author contributions

A.G. and M.P. – design and development of the research concept; A.G. – data collection, processing, econometric analysis, and verification; A.G. and M.P. – interpretation of findings; and A.G. and M.P. – writing the first draft of the article.

## Disclosure statement

The authors declare that they have no conflict of interest.

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# APPENDIX

**Table A1.** Frequency bands and corresponding periods for economic cycles

| Economic cycle | | Frequency band | Periods (in year) |
|---|---|---|---|
| Slowly fluctuating components | Long-run cycle | (0.059; 0.117) | 26.7–13.37 |
| | Business cycle | (0.117; 0.763) | 13.37–2.01 |
| Quickly fluctuating components | Short cycle | (0.763; 3.11) | <2.01 |

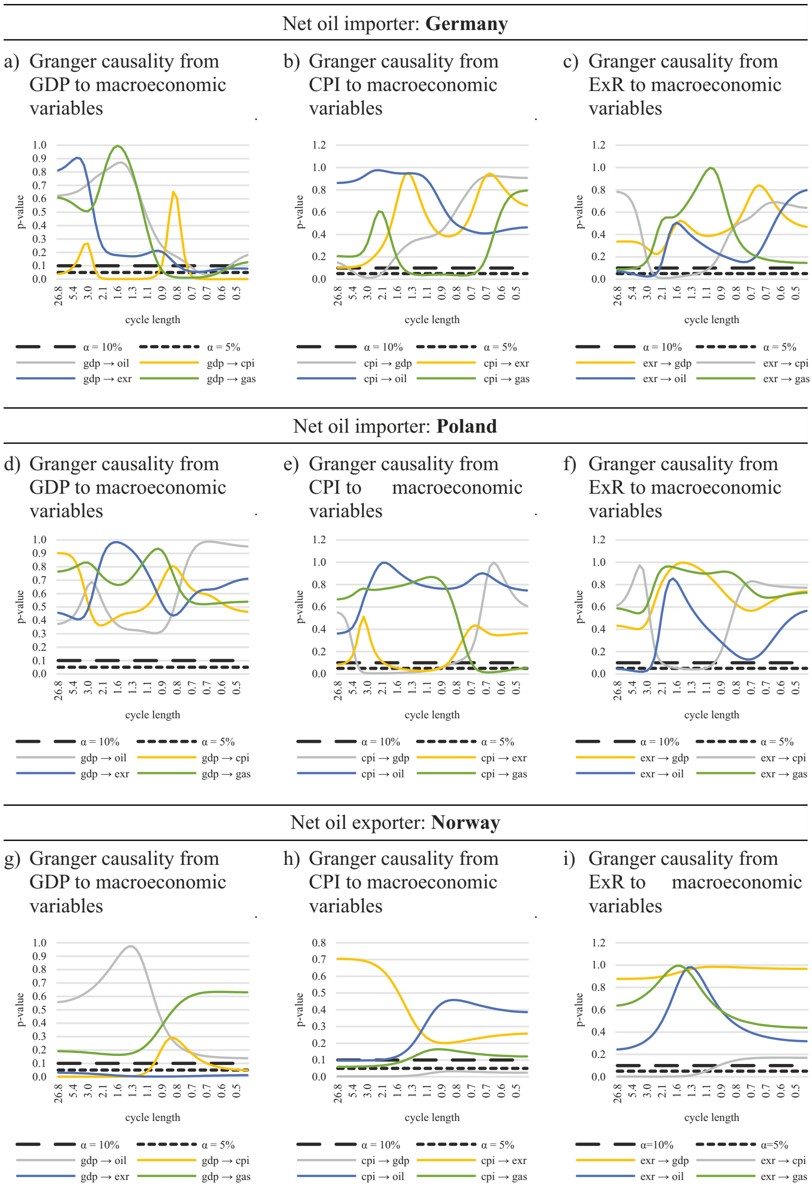


**Figure A1.** Frequency domain causality test results (p-values for Breitung-Candelon (2006) test)