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Dynamic Association between Non-Renewable Energy Matrix, Carbon Dioxide Emissions, and Economic Growth in G7 Countries: A Contribution to the Sustainable Development Goals

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ABSTRACT

This study contributes to the Sustainable Development Goals (SDGs) and the 2030 Agenda by examining CO_2 emissions and economic growth in G7 countries. The primary aim is to explore connections among coal, oil, and natural gas consumption, predicting both CO_2 emissions and economic growth despite external disruptions. The research employs vector autoregressive (VAR) and Bayesian autoregressive (BVAR) models, alongside the Granger causality test. The study tests hypotheses: (i) Fossil fuel consumption drives CO_2 emissions; (ii) Fossil fuel consumption influences economic growth; (iii) A causal link exists between CO_2 emissions and economic growth. Air pollution analysis (hypothesis i) indicates natural gas associates with CO_2 emissions in Germany, the USA, and Italy; coal links to CO_2 emissions in Canada, the USA, and Japan; CO_2 emissions due to oil connect to Canada, the USA, France, Italy, Japan, and the UK. Hypothesis ii shows natural gas consumption in Canada, the USA, France, Italy, and coal consumption in France, Italy, and the UK correlate with GDP. No GDP correlation with oil consumption is seen. Hypothesis iii reveals a two-way relationship only in Germany CO_2 emissions impact GDP and vice versa. Forecasts suggest external shocks lead to variable fluctuations up to seven periods ahead.

Keywords: SDGs, Fossil Fuels, CO_2 Emissions, Gross Domestic Product, VAR/BVAR Models
JEL Classifications: Q43, Q53, C32, Q58

1. INTRODUCTION

Energy is considered a transversal strategic input that is essential for maintaining productive and infrastructural systems. Its availability, quality, and efficiency directly influence the systemic competitiveness of nations. It represents a critical factor for socioeconomic development and energy security on a global scale. Coal, oil, and natural gas have historically constituted the primary sources used in energy generation, playing a fundamental role in supporting human activities and expanding productive capacities. In this sense, energy functions as a strategic resource with significant influence over economic stability and the geopolitical positioning of countries. Recent studies indicate that the global productive structure remains highly dependent on energy supply chains based on fossil fuels, which are essential inputs for the industrial, logistics, and transport sectors, thereby reinforcing their international economic centrality (Esen and Bayrak, 2017; Mensah et al., 2019; Becchetti et al., 2025).

The increasing demand for energy, driven by population growth and the intensification of economic activities, has resulted in the continuous exploitation of the planet's natural resources. This dynamic has consolidated a strong dependency on fossil energy sources to sustain economic performance. However, given the finite nature of these reserves, their current intensive use compromises future availability and, from an economic perspective, leads to progressively higher exploration and consumption costs. This scenario reveals a significant structural fragility, as the maintenance of economic growth based on non-renewable energy sources exacerbates the instability of international markets, increases countries' exposure to price volatility, and heightens the risk of energy supply insecurity (Rahman and Kashem, 2017; Khan et al., 2019; He et al., 2019; Mensah et al., 2019; Adedoyin et al., 2021; Diaby et al., 2025).

This study focuses on the intensification of greenhouse gas emissions, particularly carbon dioxide (CO_2), as a direct consequence of the economic growth trajectories pursued by developed countries, especially those comprising the G7. Despite possessing advanced technologies and having signed commitments to achieve net-zero emissions, these countries still face important structural challenges, such as the continued high dependence on fossil fuels and the heterogeneity in the implementation of climate policies. These challenges hinder the effective transition toward a low-carbon economy and generate tensions between sustainable development and energy security (Chen et al., 2025).

The selected countries for analysis are those of the G7 group, which, although representing approximately 10 percent of the world population, are responsible for more than 25% of global CO_2 emissions. This highlights their disproportionate contribution to climate change. The high energy demand in these countries results from a long-standing process of intensive industrialization and the adoption of sustained economic growth strategies. These patterns contrast with recent efforts aimed at implementing environmentally sustainable policies (Martins et al., 2021; Radmehr and Adebayo, 2022; Chen et al., 2025).

The primary objective of this research is to investigate the interrelationships between the consumption of coal, oil, and natural gas and their impact on CO_2 emissions, linking such consumption to economic growth under the influence of external shocks that may affect these variables. The following hypotheses will be evaluated: (i) fossil fuel consumption causes CO_2 emissions; (ii) fossil fuel consumption drives economic growth; (iii) a causal relationship exists between CO_2 emissions and economic growth.

To address these questions, simultaneous equation systems were adopted based on vector autoregressive (VAR) models, in order to capture interdependencies between variables and assess the effects of stochastic shocks within the system. VAR models are widely used in multivariate time series analysis because they allow for the examination of dynamic interactions among variables and their historical behaviors. Although these models exhibit strong predictive capabilities, they are sensitive to overparameterization when the number of variables increases, which can impair the accuracy of parameter estimation and, consequently, forecast quality (Noronha et al., 2019; Ueda et al., 2020; Elias and Ali, 2025).

To mitigate the effects of overparameterization in VAR models, Bayesian approaches provide a robust methodological alternative by incorporating prior information to enable more efficient parameter estimation. In this context, the Bayesian Vector Autoregressive (BVAR) model stands out for its ability to manage dynamic multivariate structures and is particularly suited for the analysis of complex economic systems. The introduction of prior restrictions contributes to reducing model dimensionality and improving predictive accuracy. Furthermore, BVAR models demonstrate superior performance in contexts with limited sample sizes, aligning more closely with the characteristics and constraints typical of macroeconomic data (Mohebi, 2025; Heather et al., 2025).

2. MATERIALS AND METHODS

2.1. Data and Variables

Data on coal, oil, natural gas consumption, and CO_2 emissions (CO_2) were obtained from the Statistical Review of World Energy by British Petroleum (2024), along with key development records in the world energy sector. Gross Domestic Product (GDP) data indicating economic growth were collected from The World Bank (2025) website. The sample includes 58 observations for each variable from 1965 to 2023, considering Germany, Canada, France, Japan, United States, Italy, and the United Kingdom.

The methodology utilized VAR and Bayesian VAR models to understand the short-term interrelationships among variables. The selection of the most suitable model was guided by penalizing criteria, namely the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The impulse-response function (IRF) was employed to analyze the dynamics between the time series.

The methodological procedures included: (i) applying the Variance Inflation Factor (VIF) test to detect multicollinearity, including variables in the models only if multicollinearity was absent; (ii) ensuring the series met the stationary condition through unit root tests and graphical analysis, as stable parameters over time are essential for short-term relationships; (iii) analyzing the influence among variables using the Granger causality test and the block exogeneity test to determine the degree of exogeneity and establish the variable order; (iv) estimating parameters using the maximum likelihood method after selecting the variable order and number of lags; (v) employing the impulse-response function to understand the impact of variables and the time required for stability, using two standard deviations as the impulse magnitude.

2.2. Descriptive Statistics and Multicollinearity Analysis

The application of descriptive statistics aimed to summarize and characterize the dataset through numerical measures (Lin, 2025). For this purpose, measures of central tendency and dispersion were employed. Multicollinearity remains a persistent issue in regression modeling, as it distorts the estimation of coefficients and undermines the reliability of inferential statistics (James et al., 2021; Wooldridge, 2020). To assess the degree of multicollinearity among the explanatory variables, the Variance Inflation Factor

(VIF) was calculated. In cases where high multicollinearity was identified, the implicated variables were either excluded or transformed to minimize its influence on the model.

2.3. Unit Root Test

The first step in estimating econometric models is to determine the variables' order of integration. To determine the series stability used in this research, the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979), Phillips-Perron (PP) (Phillips and Perron, 1988), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwaitkowski et al., 1992) tests were applied. The ADF and PP tests use statistics, and the null hypothesis (H_0) for both tests is that the time series has a unit root, therefore it is non-stationary. The KPSS test uses the LM (Lagrange Multiplier) statistic, and the null hypothesis (H_0) for the test is that the series is stationary. The criterion presupposes that at least two of these tests point to the same result. If the variables are not stationary, the differentiation method must be applied until they reach stationarity, after which they can be used in the model (Jenčová et al., 2025; Jowik et al., 2025).

2.4. Granger Causality Test

Causality tests were used to address temporal precedence, in the sense that a variable precedes the variations of another variable (Granger, 1974). When using the causality approach, it is necessary to understand the meaning of the cause and understand who suffers the effect. The Granger causality technique on a time series X indicates that Granger-causes another time series on Y if the forecast inaccuracy of the current Y series decreases using the X past value and the Y previous value. This procedure requires the variables to be stable. If this does not occur, the first difference should be used and then a causal examination should be performed (Ren et al., 2025; Akinwande et al., 2025).

2.5. Vector Autoregressive (VAR)

Vector autoregressive (VAR) models examine linear relationships between each variable and the lagged values of the variable itself and of all other variables, imposing as restrictions to the economic structure only the choice of the variable set and the number of relationships between them. With these models, it is possible to capture interdependence relationships that exist between variables that allow the evaluation of the impact of stochastic shocks on a given system variable (Ueda et al., 2020; Elias and Ali, 2025).

The AIC and BIC information criteria are used to determine the lag number to be included in the model. These criteria consider the residual sum of squares, the observation number, and parameter estimators; and we have that, the smaller the values, the better the model will be (Sims et al., 1996; Enders, 2008). The p-order VAR model representation follows according to Equation 1.

$$y_t = Ci + A_{11}^{(1)} y_{t-1} + \ldots + A_{ij}^{(s)} y_{t-p} + \varepsilon_{it} \tag{1}$$

Where Ci corresponds to a constant, i = 1,2,3.,n; $A_{it}^{(s)}$ represents autoregressive coefficients, and $i = j = 1,2,3.,n$; $s = 1,2,3.,p$; $y_t = y_{1t},y_{nt}$ in $t = 1,2,3.,$; and ε_{it} represents white noise residues, with $i = 1,2,3.,n$.

The selection criteria for the best model adhered to the Akaike Information Criteria (AIC) (1973) (Equation 2) and the Baeysian Information Criterion (BIC) (1978) (Equation 3).

$$AIC_p = ln\left|\sum(p)\right| + \frac{2}{T} pn^2 \tag{2}$$

$$BIC_p = ln\left|\sum(p)\right| + \frac{lnT}{T} pn^2 \tag{3}$$

Where p is the explanatory variable number considered in the model, and n is the number of observations.

VAR models have their limitations, one of which is the high parameter numbers, which are reflected in the sample size required to obtain a reliable estimate. And the other concerns are the fact that each VAR model shows that the same relationships between the variables and their lags are simultaneously compatible with several different models that also describe the contemporaneous relationships between the variables (Elias and Ali, 2025).

A simple way to ease the VAR model overparameterization is to impose that the coefficients of some variables are equal to zero and the BVAR (Bayesian Vector Autoregression) models emerged as the most satisfactory answer to the problem.

2.6. Bayesian Vector Autoregression (BVAR)

The Bayesian vector autoregressive (BVAR) model offers several advantages over the traditional vector autoregressive (VAR) model. Firstly, the BVAR model incorporates prior information, enhancing parameter estimation efficiency and reducing sensitivity to initial conditions, especially in small sample sizes. It also allows for the inclusion of time-varying parameters, capturing structural changes in economic and financial time series data (Albini et al., 2023).

Additionally, the BVAR model provides a robust framework for handling model uncertainty by generating a posterior distribution for parameters, leading to more reliable inference. Moreover, the BVAR model facilitates the estimation of unobserved variables and forecasting, making it a powerful tool for policy analysis and economic forecasting. These advantages position the BVAR model as a superior choice compared to the traditional VAR model in many empirical applications (Mohebi, 2025; Heather et al., 2025).

When using a priori, Litterman (1986) uses three of the stylized facts of macroeconomic time series: (a) Most macroeconomic time series are characterized by a trend; (b) although macroeconomic data remain persistent, the most recent lags matter the most; and (c) the lags of a variable influence the variable much more than the other variable lags (Khan et al., 2019; Chan, 2020; Van de Schoot et al., 2021).

With these three facts, Litterman (1986) derived an a priori distribution that is, in fact, a multivariate random walk. For each distribution, the prior distribution is centered in random walk specification given by Equation 4:

$$y_{n,t} = \mu_n + y_{n,t-1} + \varepsilon_{n,t} \quad (4)$$

According Chan (2020), and Van de Schoot et al. (2021), the standard priors have the following characteristics: (a) For deterministic variables, the priors are not informative, that is, flat; (b) for the endogenous variables lags, the priors are independent and normally distributed; and (c) in means prior distributions, they are zeroed. The only other prior to being defined is prior to the variance. According to Litterman (1986), the standard error in estimating the lag coefficient *l* of variable j in equation i is given by a standard deviation of the form $S(i, j, l)$, given by Equation 5:

$$S(i,j,l) = \frac{[\gamma g(l) f(i,j)]S_i}{S_j} \quad (5)$$

The complete a priori distribution can be determined if we define the value for the hyperparameter γ and define the functions *g* (*l*), as well as *f* (*i,j*). In the literature, the hyperparameter γ is known as the general prior tightness. The lag stiffness 1 with respect to lag *l* is determined by the function *g* (*l*). As the length of the delay increases, the voltage around the previous mean also increases, which is achieved by setting *g* (*l*) to decay harmonically, with *g* (*l*) = *l-d*. Finally, the function *f* (*i,j*) determines the prior adherence on variable *j* regarding the variable *i* in the syntax for variable *i* (Khan et al., 2019; Chan, 2020; Van de Schoot et al., 2021).

The estimative is based on a mixed estimative, it consists of combining the information provided by the maximum Likelihood (sample) with the proposed a priori distribution generated in the posterior distribution estimation. In this research, we assume that there is a model with N observations. In a BVAR model, "v priors" refer to the prior distributions chosen for the model parameters. The term "v priors" is an abbreviation of "vector priors" or "prior vectors." The v-observations that are related to the previous ones are weighted according to tightness degree. The more diffuse the a priori, the more BVAR estimators tend for the OLS (Van de Schoot et al., 2021; Kuschnig and Vashold, 2021).

In this research, the Litterman/Minnesota a priori distribution was chosen based on studies demonstrating its improved macroeconomic time-series forecasts (Das et al., 2022; Tsioptsia et al., 2022; Abbasian and Manoshehri, 2023). The a priori variances treat variables similarly, except for lagged dependent variables, which decrease the influence of independent autoregressive variables. The Minnesota prior assumes a prior mean of zero for coefficients in independent variables that are not self-lagged, implying a smaller influence compared to self-lagged dependent variables (Van de Schoot et al., 2021; Das et al., 2022; Abbasian and Manoshehri, 2023).

To adjust the BVAR models, different hyperparameters were tested. The Litterman/Minnesota prior consists of four hyperparameters: μ1, λ1, λ2, and λ3. μ1, the hyperparameter for the mean, is set to zero to reduce model overfitting. λ1, the constraint on variance, controls the relative importance of sample information and prior information, with a value up to 10 chosen to allow sample information to dominate. λ2 represents the variance restriction on other variables, set as 0.99 in the standard. Lastly, λ3 represents the model decay pattern, defined as 1.0 to impose linear decay (Das et al., 2022; Tsioptsia et al., 2022; Heather et al., 2025).

2.7. Impulse Response

A VAR(p) model proposes a way to allow the data, rather than the researcher, to determine the model's dynamic structure. After estimating a VAR(p), it is important to clearly characterize its dynamic structure. Impulse responses accomplish this by showing the impact of a shock to any one of the variables that filters through the model, affecting all other endogenous variables, and potentially retroactively impacting the variable itself. To calculate the impulse response, it is necessary to introduce a one-period shock in an endogenous variable and then introduce a one-period shock to the next endogenous variable. This allows us to track the effects on all variables in the model, and so on, for the other endogenous variables (Alviarez et al., 2025).

3. RESULTS AND DISCUSSION

3.1. Graphic Representation of Data, Descriptive Statistics, and Multicollinearity

The mean, minimum, maximum, standard deviation (SD), and coefficient of variation (CV) calculations of the variables are presented in Table 1.

Table 1 shows that the United States (USA) stands out significantly among the G7 countries. On average, the USA consumes 34.23 EJ of oil, 21.63 EJ of natural gas, and 16.74 EJ of coal; it emits 4,937.09 Mt of CO_2 and has a GDP of USD 9.22 trillion. When compared to the other G7 countries, these values exceed the sum of the averages for the remaining members. The total average for the other G7 countries amounts to 12.71 EJ of coal, 29.82 EJ of oil, 17.99 EJ of natural gas, and 3,766.81 Mt of CO_2. Only the group's total average GDP (USD 10.41 trillion) surpasses that of the USA (USD 9.22 trillion).

The coefficient of variation (CV) indicates high dispersion for GDP (64.2-80.4%), which is corroborated by the graphical analysis (Figure 1), showing a steady upward trend in this variable across all countries. Natural gas consumption also shows high variability (CV between 19% and 69%), reflecting its growing importance as a primary energy source in the transition toward sustainability. This increase in demand has been driven by the need to reduce greenhouse gas emissions and combat air pollution (Nakajima and Toyoshima, 2019).

Coal consumption exhibits moderate dispersion (CV ranging from 25% to 55%), as most countries maintain relatively stable patterns, except for the USA, which experienced a peak of 22.85 EJ between 2005 and 2007 and has remained the main global consumer of coal, despite a downward trend in recent years. In contrast, oil consumption (CV between 11% and 21%) and CO_2 emissions (CV between 12% and 19%) present low variability, making them the most stable variables in the dataset.

Table 1: Descriptive statistics for the variables CO_2, coal, natural gas, oil, and gross domestic product

Descriptive statistics	Canada	United States	France	Germany	Italy	Japan	United Kingdom
Variable:				CO_2 emissions			
Mean	464.84	4937.09	379.29	901.11	370.47	1046.63	562.70
Median	457.38	4970.49	370.50	896.93	377.16	1084.12	573.24
Maximum	574.99	5884.22	518.82	1116.42	470.20	1293.79	728.68
Minimum	260.33	3451.89	251.55	571.90	204.87	446.90	316.91
Standard Deviation	85.83	570.62	64.18	139.15	57.91	201.48	101.43
CV	0.18	0.12	0.17	0.15	0.16	0.19	0.18
Variable:				Coal consumption			
Mean	0.93	16.74	0.80	4.48	0.49	3.58	2.18
Median	0.98	17.30	0.65	4.00	0.51	3.40	1.99
Maximum	1.34	22.85	1.73	6.73	0.70	5.10	4.92
Minimum	0.37	8.20	0.18	1.81	0.21	1.96	0.18
Standard Deviation	0.26	4.18	0.42	1.41	0.12	1.07	1.20
CV	0.28	0.25	0.52	0.32	0.25	0.30	0.55
Variable:				Natural gas consumption			
Mean	2.62	21.63	1.14	2.34	1.71	2.12	2.23
Median	2.69	21.38	1.22	2.57	1.76	2.14	2.42
Maximum	4.46	31.91	1.78	3.31	2.98	4.49	3.67
Minimum	0.78	14.97	0.11	0.11	0.27	0.07	0.03
Standard Deviation	1.02	4.09	0.46	0.92	0.86	1.46	1.05
CV	0.39	0.19	0.41	0.39	0.51	0.69	0.47
Variable:				Oil consumption			
Mean	3.85	34.23	3.82	5.40	3.53	9.36	3.51
Median	3.87	34.76	3.85	5.45	3.84	9.70	3.48
Maximum	4.73	40.37	5.42	7.02	4.41	11.93	4.84
Minimum	2.31	23.09	2.29	3.67	2.11	3.65	2.35
Standard Deviation	0.62	3.77	0.69	0.77	0.69	1.95	0.49
CV	0.16	0.11	0.18	0.14	0.20	0.21	0.14
Variable:				Gross domestic product			
Mean	8.16E+11	9.22E+12	1.43E+12	2.03E+12	1.15E+12	3.18E+12	1.45E+12
Median	6.06E+11	7.29E+12	1.37E+12	2.08E+12	1.18E+12	1.18E+12	1.18E+12
Maximum	2.16E+12	2.77E+13	3.05E+12	4.53E+12	2.42E+12	6.27E+12	3.38E+12
Minimum	5.46E+10	7.42E+11	1.01E+11	3.16E+11	7.07E+10	9.73E+10	1.02E+11
Standard Deviation	6.56E+11	7.38E+12	1.00E+12	1.40E+12	7.90E+11	2.04E+12	1.10E+12
CV	8.04E-01	8.00E-01	6.99E-01	6.90E-01	6.87E-01	6.42E-01	7.59E-01

Source: Authors (2025)

The variance inflation factor (VIF) was calculated to investigate the collinearity between the selected variables, and we found that the variables are linearly independent (VIF $\cong$ 1). Therefore, all variables can be used in the model without exclusion. Although some variables exhibit large fluctuations, there is no evidence of abrupt breaks. Hence, conventional unit root tests will be used.

3.2. Unit Root Test

In addition to the evidence of non-stationarity shown in the graphical analysis for some series, the unit root tests, such as the Augmented Dickey-Fuller (ADF) test - (t-stat) (null hypothesis: the variable has a unit root), Phillips-Perron (PP) test - (t-stat) (null hypothesis: the variable has a unit root), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test - (LM-stat) (null hypothesis: the variable is stationary), were conducted at a 5% significance level, as presented in Table 2.

We observed that the variables "oil consumption" for Japan and the USA, "natural gas consumption" for Germany, and "CO_2 emissions" for Japan are level stable (I = 0), thus indicating that these variables do not show significant variations over time or trend, highlighting a consistent consumption pattern. Due to their high variability, the "coal consumption" and "GDP" of the USA required two differences (I = 2) to become level stable. The large fluctuations in coal consumption in the USA can be attributed to its increasing behavior, reaching a peak between 2005 and 2007, and showing a sharp decline in consumption since then, as evidenced by Vulin et al. (2020) and Sesso et al. (2022).

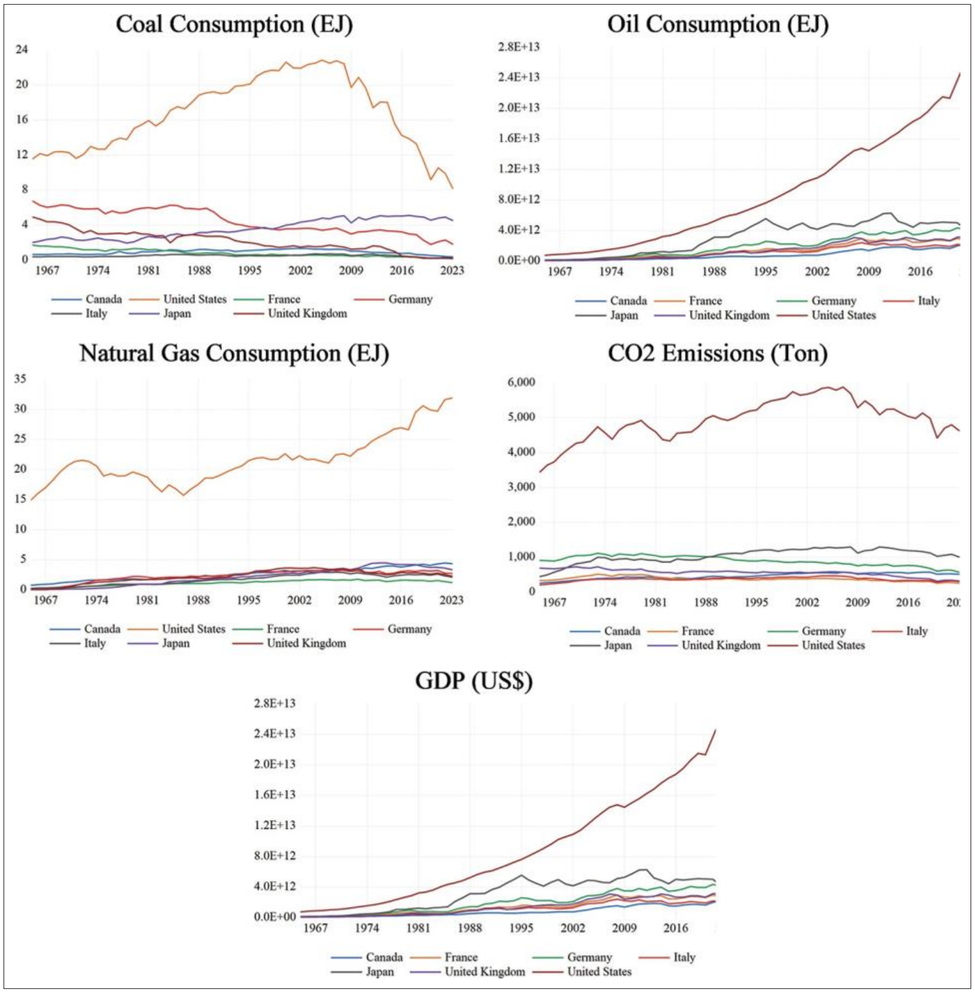
The other variables displayed oscillations in behavior, but with only one difference (I = 1) they became level stable. Based on the identification of the series' stability, the Granger causality test was applied to determine the causal relationships between the variables, and only the significant variables were selected to be included in the model.

3.4. Granger Causality Test

Causality tests were used to identify the existence of unidirectional causality, bidirectional causality, and the non-existence of causality. The results are displayed in Table 3.

Through the Granger causality test, we found that all the variables have a causal relationship, making it relevant for them to remain in the model, as they contribute to improving the forecast. The results show that in Germany, natural gas and GDP are related to CO_2 emissions, while CO_2 emissions are related to GDP. In Canada,

Figure 1: The original series graph for coal, oil, natural gas, CO_2, and GDP



Source: Authors (2025)

CO_2 emissions are related to coal and oil consumption, while GDP is related to natural gas and also CO_2 emissions. In the USA, CO_2 emissions are related to coal, oil, and natural gas, while only natural gas is linked to GDP. In France, coal and oil are related to CO_2, and CO_2, coal, and natural gas are related to GDP. In Italy, oil and natural gas consumption is related to CO_2 emissions, and CO_2, natural gas, and coal are related to GDP. In Japan, coal and oil consumption are related to CO_2, and CO_2 is related to GDP. In the United Kingdom, oil consumption is related to CO_2 emissions, and CO_2 emissions and coal consumption are related to GDP.

We found that the economic growth of Germany, France, Italy, and Japan is associated with CO_2 emissions. CO_2 emissions in Canada, USA, France, and Japan are mainly related to coal and oil consumption. In Germany, the USA, and Italy, the natural gas consumption is associated with CO_2 emissions. Only in Germany a bidirectional relationship was identified, in which economic growth (GDP) causes CO_2 emissions and CO_2 emissions cause economic growth (GDP).

After identifying the causal relationships, the block exogeneity test was intuitively applied to classify the variables according to their exogeneity, with the aim of improving the model's accuracy.

3.5. Block Exogeneity Test

The block exogeneity test, which allows the classification of variables in relation to their exogeneity, is shown in Table 4.

By using the block exogeneity test, the variables with the highest Chi-square - Chi-square (χ^2) and lowest P-value are the most exogenous variables. Thus, the models were estimated according to Table 5, presented below:

3.6. VAR and BVAR Modeling

With defined model order and number of lags to be included, we estimated the parameters using both a VAR and a BVAR model (following the Litterman/Minnesota a priori) for each country. This was done in order to determine the short-term relationship between variables with as little error as possible. The VAR models are shown in Table 6, while the BVAR models are shown in Table 7. We selected the model with the smallest AIC and BIC values as our final model.

The VAR models were tested with and without the constant presence, and those with the lowest AIC and BIC values were selected. Starting from the selected VAR model, the BVAR models were also considering or not the constant presence.

Table 2: ADF, PP, and KPSS unit root tests

Germany	ADF			PP			KPSS			Decision
Variable	Level	1st difference	t-calc	Level	1st difference	t-calc	Level	1st difference	LM-stat	
Coal	0.1398	*−5.1666*	−2.9224	−0.0488	*−5.1555*	−2.9224	0.8783	*0.1127*	0.4630	I (1)
Oil	−0.6468	*−5.1660*	−2.9237	−0.6534	*−6.4043*	−2.9224	0.7793	*0.1415*	0.4630	I (1)
Natural gas	*−3.5776*	–	−2.9211	−3.7335	-	−2.9211	0.8517	*0.4637*	0.4630	I (0)
CO_2	0.7845	*−7.1584*	−2.9211	1.1730	*−7.1617*	−2.9211	0.9438	*0.2532*	0.4630	I (1)
GDP	−0.6151	*−6.4862*	−2.9211	−0.6151	*−6.4872*	−2.9211	0.9303	*0.0445*	0.4630	I (1)
Canada	**ADF**			**PP**			**KPSS**			**Decision**
Variable	**Level**	**1st difference**	**t-calc**	**Level**	**1st difference**	**t-calc**	**Level**	**1st difference**	**LM-stat**	
Coal	−0.7685	*−7.0106*	−2.9155	−0.8259	*−7.0201*	−2.9165	*0.2989*	-	0.4630	I (1)
Oil	−2.4074	*−3.9395*	−2.9165	−2.4142	*−3.9395*	−2.9155	0.8786	*0.2368*	0.4630	I (1)
Natural gas	−0.7489	*−7.8369*	−2.9176	−1.0986	*−8.6088*	−2.9155	0.9116	*0.2134*	0.4630	I (1)
CO_2	−2.7007	*−5.2394*	−2.9155	−2.6668	*−5.2598*	−2.9155	0.8578	*0.4400*	0.4630	I (1)
GDP	0.0427	−5.3393	−2.9155	0.0427	*−5.2436*	−2.9155	0.8332	0.1791	0.4630	I (1)
EUA	**ADF**			**PP**			**KPSS**			**Decision**
Variable	**Level**	**1st difference**	**t-calc**	**Level**	**1st difference**	**t-calc**	**Level**	**1st difference**	**LM-stat**	
Coal	−1.6164	0.5591	−2.9211	−0.8462	*−6.0715*	−2.9165	0.5460	0.6750	0.4630	I (2)
Oil	-	-	−2.9165	-	-	−2.9155	0.6159	*0.3294*	0.4630	I (0)
Natural gas	0.0922	*−5.9954*	−2.9155	−0.3281	*−6.0214*	−2.9155	0.7992	*0.1535*	0.4630	I (1)
CO_2	−2.5991	*−4.9533*	−2.9155	−2.5625	*−4.7587*	−2.9155	0.7285	0.6384	0.4630	I (1)
GDP	2.4572	−1.6337	−2.9176	4.7337	*−3.0956*	−2.9155	0.8843	0.8715	0.4630	I (2)
France	**ADF**			**PP**			**KPSS**			**Decision**
Variable	**Level**	**1st difference**	**t-calc**	**Level**	**1st difference**	**t-calc**	**Level**	**1st difference**	**LM-stat**	
Coal	−1.6864	*−8.3044*	−2.9165	−1.6834	*−8.2842*	−2.9165	0.8911	*0.1471*	0.4630	I (1)
Oil	−1.8059	*−4.0026*	−2.9165	−2.3491	*−3.9827*	−2.9165	*0.2960*	-	0.4630	I (1)
Natural gas	−2.6387	*−9.1631*	−2.9165	−2.3922	*−9.1374*	−2.9165	0.8434	0.5539	0.4630	I (1)
CO_2	−0.3872	*−5.8317*	−2.9165	−0.9423	*−6.0663*	−2.9165	0.5715	*0.3289*	0.4630	I (1)
GDP	−0.5022	*−6.2845*	−2.9165	−0.5371	*−6.2845*	−2.9165	0.8672	*0.0785*	0.4630	I (1)
Italy	**ADF**			**PP**			**KPSS**			**Decision**
Variable	**Level**	**1st difference**	**t-calc**	**Level**	**1st difference**	**t-calc**	**Level**	**1st difference**	**LM-stat**	
Coal	−0.5570	*−5.4680*	−2.9165	−1.0917	*−5.4680*	−2.9165	0.2576	-	0.4630	I (1)
Oil	−0.8596	*−3.4678*	−2.9165	−1.5804	*−3.3798*	−2.9165	0.3643	-	0.4630	I (1)
Natural gas	−1.4997	*−6.1926*	−2.9165	−1.4324	*−6.2681*	−2.9165	0.8412	*0.2525*	0.4630	I (1)
CO_2	−2.7952	*−3.9525*	−2.9165	−2.6602	*−3.9216*	−2.9165	0.3542	-	0.4630	I (1)
GDP	−0.8587	*−6.1147*	−2.9165	−0.8804	*−6.1265*	−2.9165	0.8566	*0.1095*	0.4630	I (1)
Japan	**ADF**			**PP**			**KPSS**			**Decision**
Variable	**Level**	**1st difference**	**t-calc**	**Level**	**1st difference**	**t-calc**	**Level**	**1st difference**	**LM-stat**	
Coal	−1.0545	*−8.8484*	−2.9165	−1.0157	*−8.8615*	−2.9165	0.8599	*0.1097*	0.4630	I (1)
Oil	*−2.9693*	-	−2.9155	−2.8206	*−3.9355*	−2.9155	0.2196	-	0.4630	I (0)
Natural gas	−0.6890	*−5.1722*	−2.9155	−0.6936	*−5.1073*	−2.9165	0.8792	*0.1524*	0.4630	I (1)
CO_2	*−3.6278*	-	−2.9165	*−3.5761*	-	−2.9155	0.8649	0.6123	0.4630	I (0)
GDP	−1.1236	*−5.3765*	−2.9165	−1.1263	*−5.1054*	−2.9155	0.8279	0.1593	0.4630	I (1)
United Kingdom	**ADF**			**PP**			**KPSS**			**Decision**
Variable	**Level**	**1st difference**	**t-calc**	**Level**	**1st difference**	**t-calc**	**Level**	**1st difference**	**LM-stat**	
Coal	−1.4512	*−7.6784*	−2.9165	−1.4519	*−7.8674*	−2.9165	1.0117	*0.1167*	0.4630	I (1)
Oil	−1.0429	*−5.9991*	−2.9165	−1.0429	*−5.8603*	−2.9165	0.6324	*0.2264*	0.4630	I (1)
Natural gas	−2.4845	*−6.1157*	−2.9165	−2.2363	*−6.4729*	−2.9165	0.7465	*0.4278*	0.4630	I (1)
CO_2	1.0764	*−7.4440*	−2.9165	1.4980	*−7.4438*	−2.9165	0.8944	*0.2996*	0.4630	I (1)
GDP	0.0446	*−4.9146*	−2.9165	−0.3636	*−5.0645*	−2.9165	0.8669	0.1117	0.4630	I (1)

Note: Italicized values indicate the order of integration of the series, based on unit root test results. At level, they denote stationarity without transformation; at first difference, stationarity is achieved after differencing. The symbol (–) indicates stationarity at level, making further testing unnecessary.
Source: Authors (2025)

The BVAR model coefficients following the Litterman/Minessota a priori presented lower information criteria than those of the conventional VAR model and, therefore, were selected to carry out the estimates.

Table 3: Granger causality test

Germany				
NullHypothesis			F-statistic	Prob
CO_2	→	Oil	4.3835	0.0418
Natural Gas	→	CO_2	3.7924	0.0576
GDP	→	CO_2	2.0910	0.1550
CO_2	→	GDP	2.2121	0.1438
Coal	→	Oil	3.2012	0.0802
Natural Gas	→	Oil	2.1482	0.1495
Coal	→	Natural Gas	1.9123	0.1434
GDP	→	Coal	2.7007	0.1071

France				
NullHypothesis			F-statistic	Prob
Coal	→	CO_2	10.9381	0.0017
Oil	→	CO_2	14.1670	0.0004
CO_2	→	GDP	1.8154	0.1538
Coal	→	Oil	8.0944	0.0064
Coal	→	GDP	4.5721	0.0373
Oil	→	Natural Gas	1.9382	0.1699
GDP	→	Natural Gas	1.5336	0.1412
Natural Gas	→	GDP	6.3543	0.0149

Canada				
NullHypothesis			F-statistic	Prob
Oil	→	Coal	2.2374	0.0812
Coal	→	CO_2	1.9161	0.1255
Natural Gas	→	Oil	3.9766	0.0080
Oil	→	Natural Gas	3.1754	0.0229
CO_2	→	Oil	3.6484	0.0122
Oil	→	CO_2	7.2214	0.0002
GDP	→	Oil	2.3148	0.0731
Natural Gas	→	GDP	6.0319	0.0006
CO_2	→	GDP	2.0497	0.1047

Italy				
NullHypothesis			F-statistic	Prob
Oil	→	CO_2	7.5706	0.0082
Natural Gas	→	CO_2	1.97482	0.166
CO_2	→	GDP	5.47453	0.0232
Oil	→	Natural Gas	1.87216	0.1772
Natural Gas	→	GDP	10.1869	0.0024
Coal	→	GDP	2.11837	0.1517

Japão				
NullHypothesis			F-statistic	Prob
Coal	→	Oil	3.3316	0.0442
Coal	→	Natural Gas	1.83847	0.1401
Coal	→	CO_2	2.60922	0.0840
CO_2	→	Oil	6.02716	0.0046
Oil	→	CO_2	2.43111	0.0985
CO_2	→	GDP	1.97724	0.1496

EUA				
NullHypothesis			F-statistic	Prob
Oil	→	Coal	2.4433	0.0618
Coal	→	Oil	1.9567	0.1093
Coal	→	Natural Gas	4.1501	0.0065
CO_2	→	Coal	2.4910	0.0579
Coal	→	CO_2	5.6872	0.0010
Natural Gas	→	Oil	2.3078	0.0738
Oil	→	CO_2	4.1214	0.0066
Natural Gas	→	CO_2	2.9216	0.0321
Natural Gas	→	GDP	4.1305	0.0067

United Kingdom				
NullHypothesis			F-statistic	Prob
Oil	→	CO_2	3.40004	0.071
CO_2	→	GDP	2.52512	0.1182
Natural Gas	→	Coal	2.25511	0.1393
Coal	→	Natural Gas	2.34259	0.1321
Coal	→	GDP	2.80181	0.1003

The symbol→indicates unidirectional causality; Null Hypothesis: series "X" does not cause series "Y" in the direction of Granger; Alternative Hypothesis: series "X" causes series "Y" in the direction of Granger; $\alpha=0.15$

Source: Authors (2025)

3.7. Impulse Response Function

The BVAR models displayed the best results and were selected for the impulse-response analysis. This function graphically represents the future behavior of the variables. In line with the research purpose, which is to analyze the influence of fossil fuel consumption on CO_2 emissions and economic growth, we analyzed the responses of CO_2 and GDP to random disturbances caused in coal, oil, and natural gas consumption for the next 10 periods, as shown in Figure 2.

When analyzing Figure 2, we identified that:

- In Germany, the results indicate, after external shocks occur, that CO_2 emissions tend to increase due to disturbances in the consumption variables of coal, oil, and natural gas, and they should continue to fluctuate for the next six periods (i.e., 6 years) before stabilizing from the seventh period onwards. Disturbances in GDP lead to a reduction in CO_2 emissions in the first three periods, followed by an increase in emissions. The response of GDP to the shocks in the variables shows that natural gas consumption has an immediate negative effect on GDP, but after a period and a half, it tends to have positive effects. Oil has a positive effect, while coal consumption has a negative effect on economic growth. The response of GDP to a shock in CO_2 emissions is a slight increase, which tends to decline after two periods and continue to fluctuate until the tenth period, where it reaches stability. Similar studies have found correlation between fossil fuel consumption, economic growth, and CO_2 emissions, corroborating the results of this research (Paraschiv and Paraschiv, 2020; Tugcu and Topcu, 2018; Apergis and Payne, 2012; Shafiei and Salim, 2014).
- In Canada, GDP and natural gas consumption have a positive effect on CO_2 emissions in the first period, as evidenced by Rahman and Vu (2020), but after two periods, oil and coal consumption also have a negative effect on CO_2 emissions. When analyzing economic growth, all variables tend to have a negative effect on GDP. This result may be related to the Canadian government's constant improvement of renewable energy development policies, which has resulted in stable demand for renewable energy (Xu et al., 2019).
- In the USA, projections show that the coal consumption tends to reduce CO_2 emissions for up to 2 years, after which it increases significantly and remains oscillating for the next

Table 4: Block exogeneity test

Germany				Italy			
Variable	Chi-square (χ^2)	df	Prob	Variable	Chi- square (χ^2)	df	Prob
CO_2	5.887381	2	0.0527	CO_2	7.077335	1	0.0078
Oil	5.690654	2	0.0581	Oil	6.719277	1	0.0095
Coal	5.367273	2	0.0683	Natural Gas	5.460589	1	0.0195
Natural Gas	3.556014	2	0.1690	GDP	1.083956	1	0.2978
GDP	2.450308	2	0.2937	Coal	0.888226	1	0.3460
Canada				**Japan**			
Variable	Chi-square (χ^2)	df	Prob	Variable	Chi-square (χ^2)	df	Prob
Oil	19.12112	4	0.0007	Oil	3.18601	1	0.0743
CO_2	12.10709	4	0.0166	CO_2	2.710218	1	0.0997
GDP	8.202724	4	0.0844	Coal	2.265917	1	0.1322
Natural Gas	8.108887	4	0.0877	Natural Gas	1.128685	1	0.2881
Coal	7.846201	4	0.0974	GDP	0.898753	1	0.3431
EUA				**United Kingdom**			
Variable	Chi-square (χ^2)	df	Prob	Variable	Chi-square (χ^2)	df	Prob
Coal	13.3186	4	0.0098	CO_2	14.46684	1	0.0001
Natural Gas	7.7242	4	0.1022	Coal	2.503984	1	0.1136
GDP	6.7787	4	0.1481	Natural Gas	2.411207	1	0.1205
Oil	3.2137	4	0.05227	Oil	2.028523	1	0.1544
CO_2	2.564761	4	0.6331	GDP	0.314441	1	0.5750
France							
Variable	Chi-square (χ^2)	df	Prob				
Natural Gas	4.122086	1	0.0423				
Oil	3.314925	1	0.0687				
CO_2	2.427019	1	0.1193				
GDP	1.229044	1	0.2676				
Coal	0.703228	1	0.4017				

Fonte: Authors (2025)

Table 5: Estimated model order by country

Country	Estimated model order	Lag length criteria
Germany	Δ(co) Δ(oil) Δ(coal) gas Δ(gdp)	1
Canada	Δ(oil) Δ(co) Δ(gdp) Δ(gas) Δ(coal)	4
EUA	Δ(co) Δ(gdp, 2) Δ(coal, 2) Δ(gas) Δ(oil)	4
France	Δ(gas) Δ(oil) Δ(co) Δ(gdp) Δ(coal)	1
Italy	Δ(co) Δ(oil) Δ(gas) Δ(gdp) Δ(coal)	1
Japan	oil co Δ(coal) Δ(gas) Δ(gdp)	1
United Kingdom	Δ(co) Δ(coal) Δ(oil) Δ(gas) Δ(gdp)	1

Source: Authors (2025)

periods. The same effect can be observed in natural gas consumption and GDP, which, although showing a reduction in the first three periods, tend to increase and follow an oscillatory behavior with no stabilization prospect. Natural gas consumption tends to reflect an increase in CO_2 emissions for up to 2 years, after which it reduces and continues to fluctuate. The shocks caused by CO_2 emissions lead to a reduction in GDP, making it a more representative variable in the analysis. Coal and natural gas consumption reflect a reduction in GDP for up to 2 years, but between 2 and 3 years they tend to cause an increase in GDP, which will continue to fluctuate for the next few years. Natural gas consumption reflects an immediate increase in GDP, but after 2 years it continues to fluctuate.

- In France, the consumption of oil, gas, and coal, as well as GDP, tends to result in a reduction in CO_2 emissions immediately after an external shock. However, in the third period, these variables tend to have a positive effect on emissions, as observed in a study by Omri and Saadaoui (2023), and they reach stability around the eighth period. Gas and coal consumption tend to boost GDP, which also reflects in CO_2 emissions. Oil consumption, on the other hand, tends to decrease GDP for a period of 4 years before reaching stability. It is worth noting that France has focused on nuclear energy and electricity development, despite the availability of renewable resources like hydro and biomass (Millot et al., 2020), to promote energy independence and cost competitiveness while reducing oil consumption.
- In Italy, the country previously adopted nuclear energy to save fossil fuel usage but abandoned it after the Chernobyl accident. Currently, Italy uses fossil fuels and renewable sources, with fossil fuels and their participation in GDP and CO_2 emissions being reiterated in a study by Bersano et al. (2020). The study shows that oil and coal consumption lead to an increase in CO_2 emissions within 2 years, and natural gas consumption does not affect emissions within two periods, but has a decaying effect that reaches stability in up to seven periods. Coal and

Table 6: Classic VAR model and its respective penalizing criteria

Country	Lag	Model		AIC	BIC
Germany	1-1 lags	Δ(co) Δ(oil) Δ(coal) gas Δ(gdp)*	With constant	61.124	62.180
		Δ(co) Δ(oil) Δ(coal) gas Δ(gdp)	Without constant	61.215	62.283
Canada	1-4 lags	Δ(oil) Δ(co) Δ(gdp) Δ(gas) Δ(coal)*	With constant	53.101	57.078
		Δ(oil) Δ(co) Δ(gdp) Δ(gas) Δ(coal)	Without constant	53.792	57.579
EUA	1-4 lags	Δ(co) Δ(gdp, 2) Δ(coal, 2) Δ(gas) Δ(oil)	With constant	71.050	75.070
		Δ(co) Δ(gdp, 2) Δ(coal, 2) Δ(gas) Δ(oil)*	Without constant	70.960	74.780
France	1-1 lags	Δ(gas) Δ(oil) Δ(co) Δ(gdp) Δ(coal)*	With constant	54.281	55.386
		Δ(gas) Δ(oil) Δ(co) Δ(gdp) Δ(coal)	Without constant	54.524	55.445
Italy	1-1 lags	Δ(co) Δ(oil) Δ(gas) Δ(gdp) Δ(coal)	With constant	53.473	54.578
		Δ(co) Δ(oil) Δ(gas) Δ(gdp) Δ(coal)*	Without constant	53.418	54.339
Japan	1-1 lags	oil co Δ(coal) Δ(gas) Δ(gdp)*	Withc onstant	63.281	64.386
		oil co Δ(coal) Δ(gas) Δ(gdp)	Without constant	63.519	64.440
United Kingdom	1-1 lags	Δ(co) Δ(coal) Δ(oil) Δ(gas) Δ(gdp)*	With constant	58.673	59.778
		Δ(co) Δ(coal) Δ(oil) Δ(gas) Δ(gdp)	Without constant	58.816	59.737

Asterisks (*) indicate the selected model based on the best performance according to the lowest AIC or BIC value
Source: Author (2025)

Table 7: Bayesian VAR model using Litterman/Minnesota a priori and their respective penalizing criteria

Criteria		AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC
Country	Lagdecay	Overaltightness-0.1		Overaltightness-1		Overaltightness-5		Overaltightness-10	
Germany	1	50.7829	52.7175	49.9368	51.8714	49.8694	51.8039	49.8690*	51.8036*
	0	50.6944	52.6290	49.9141	51.8487	49.8691	51.8037	49.8690*	51.8035*
Canada	1	42.9731	44.8493	41.6046	43.4808	41.5448*	43.4210*	41.5467	43.4229
	0	42.7021	44.5783	41.5555	43.4317	41.5443*	43.4205*	41.5468	43.4230
EUA	1	64.3391	66.2153	62.3676	64.2438	62.3078*	64.1836*	62.3084	64.1846
	0	63.9876	65.8638	62.3509	64.2271	62.3079*	64.1839*	62.3083	64.1845
France	1	45.1770	47.0186	44.6391	46.4808	44.5997	46.4414	44.5994*	46.4411*
	0	45.1770	47.0186	44.6391	46.4808	44.5997	46.4414	44.5994*	46.4411*
Italy	1	43.4542	45.2958	42.9530	44.7946	42.9345	44.7761	42.9344*	44.7761*
	0	43.4542	45.2958	42.9530	44.7946	42.9345	44.7761	42.9344*	44.7761*
Japan	1	53.9953	55.8369	53.0426	54.8843	53.0023*	54.8459*	53.0044	54.8461
	0	53.9817	55.8233	53.0254	54.8670	53.0026*	54.8459*	53.0044	54.8460
UK	1	49.6221	51.4637	49.4180	51.2596	49.3498	51.1914	49.3488*	51.1905*
	0	49.6221	51.4637	49.4180	51.2596	49.3498	51.1914	49.3488*	51.1905*

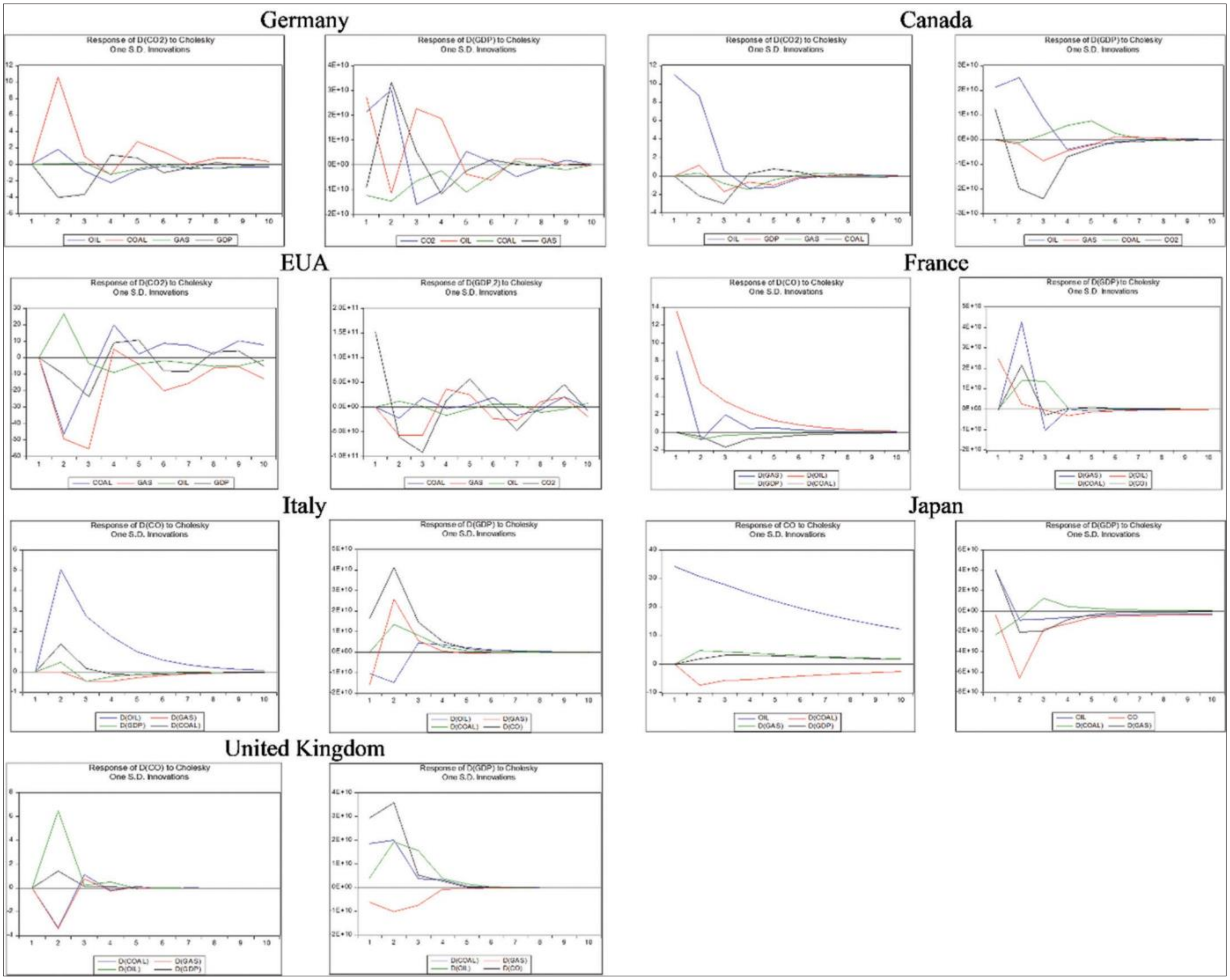
Asterisks (*) indicate the best-performing values based on the lowest AIC or BIC criteria. These values help identify the most appropriate Bayesian VAR model specification for each country
Source: Authors (2025)

natural gas consumption, along with CO_2 emissions, cause an increase in GDP when subjected to external shocks, while oil consumption reduces GDP for up to 2 years, before causing a slight increase and reaching stability in up to seven periods.

- In Japan, oil consumption initially has a positive effect on CO_2 emissions, which then tends to decrease. Fossil fuels constitute about 87% of Japan's energy mix, with oil being the most widely used (40%) (Adebayo et al., 2021), while natural gas and coal are becoming more crucial to offset nuclear shortages. Coal has an immediate negative impact on CO_2 emissions but slowly recovers, while natural gas consumption and GDP become the primary factors responsible for increasing these emissions. CO_2 emissions have a negative effect on GDP, while natural gas and oil consumption have positive effects that tend to slowly decline, reaching stability from the fifth period onwards. Coal consumption has an immediate negative effect on GDP, but it causes an increase in GDP between the second and third periods.
- In the United Kingdom, oil consumption and economic growth boost CO_2 emissions immediately, with similar results found in a study by Paraschiv and Paraschiv (2020), while gas and coal consumption show the opposite behavior by reducing emissions in the second period, but then positively affecting CO_2 emissions from the third period onwards. Coal consumption, oil, and CO_2 emissions have a positive impact on economic growth, while natural gas consumption has a negative effect. Faced with the relationship between fossil fuels and CO_2 emissions, the United Kingdom has implemented several strategies to increase the use of renewable energy and mitigate fossil fuels, such as enacting a carbon tax, shifting electricity production to renewable sources, and reducing coal consumption (Adebayo et al., 2022).

When analyzing the effects of fossil fuel consumption on economic growth and CO_2 emissions, it is evident that these effects fluctuate over time, and in most countries, the oscillation lasts up to seven periods until reaching stability. Due to possible impacts caused by external shocks, these effects may differ in each country in the coming years and can be negative or positive.

Figure 2: CO_2 and GDP response given the random disturbances caused in the consumption of coal, oil and natural gas for 10 periods ahead



Source: Authors (2025)

4. CONCLUSION

This research aimed to assess the interdependencies among coal, oil, and natural gas consumption in relation to energy consumption, specifically focusing on the impact on air pollution (CO_2 emissions) and economic growth (GDP), while accounting for potential external disturbances. The motivation behind this study was the concern over greenhouse gas emissions resulting from economic growth in developed nations.

Bayesian VAR models were found to have lower penalizing criteria than Classic VAR models for all countries, making them more efficient and suitable for projections. The projections for CO_2 emissions and GDP varied for each country. Fossil fuels were found to be crucial for the economic aspect of some countries, while in others, they had negative environmental effects without contributing to economic growth, leading to CO_2 emissions.

The evaluations considered were: (i) Fossil fuel consumption causes CO_2 emissions; (ii) fossil fuel consumption causes economic growth; and (iii) there is a causal relationship between CO_2 emissions and economic growth.

In analyzing air pollution (hypothesis i), natural gas consumption was associated with CO_2 emissions in Germany, the USA, and Italy, while coal consumption was associated with CO_2 emissions in Canada, the USA, and Japan. Additionally, CO_2 emissions due to oil consumption were associated with CO_2 emissions in Canada, the USA, France, Italy, Japan, and the United Kingdom.

Regarding economic growth (hypothesis ii), natural gas consumption was associated with GDP in Canada, the USA, France, and Italy, while coal consumption was associated with GDP in France, Italy, and the United Kingdom. No country showed an association between GDP and oil consumption.

Analyzing the relationship between economic growth and controlled air pollution (hypothesis iii), only Germany exhibited a bidirectional relationship, with CO_2 emissions associated with GDP and GDP with CO_2 emissions.

The empirical findings consistently support the superiority of BVAR models over traditional VAR models in various scientific domains. With their ability to incorporate informative priors, accommodate time-varying parameters, handle model uncertainty, and forecast unobserved variables, BVAR models provide a robust framework for policy analysis and economic forecasting. Their flexibility and efficiency make them essential tools for further economic analysis and understanding complex interrelationships among variables.

These research findings directly connect to the United Nations' Sustainable Development Goals (SDGs), specifically contributing to SDG 7 (Affordable and Clean Energy), SDG 13 (Climate Action), and SDG 8 (Decent Work and Economic Growth). Addressing the environmental and economic challenges related to CO_2 emissions aligns with global commitments to combat climate change and pursue sustainable development in line with the principles of the SDGs.

For future research, it is suggested to explore the representativeness of renewable and non-renewable resources in economic growth and air pollution by incorporating renewable resources. Additionally, expanding the analysis to other countries, such as the BRICS countries, would provide a broader perspective.

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