THE CAUSALITY RELATIONSHIP BETWEEN ENERGY CONSUMPTION AND GDP GROWTH IN FIVE COUNTRIES.

UNIVERSITY OF BRESCIA

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Introduction and Background of the Project

In recent years, **energy consumption** and **GDP** growth rate have gained increasing importance. Energy consumption is crucial for economic growth, while GDP serves as a key indicator of a country's economic health. Understanding the relationships between energy consumption and GDP growth is essential for developing sustainable energy policies and guiding economic planning.

Understanding the type of causality between gdp and a country's energy consumption helps to make significant political decisions.

- For example, if uni-directional causality runs from **energy consumption to GDP**, then this is indicative of energy-dependent economy;
- By contrast, if uni-directional causality runs **from GDP to energy**, then this denotes a less energy-dependent economy, one where the implementation of energy conservation policies would have few, if any, adverse effects on income;
- Finally, as for the finding of **no causality in either direction**, would signify that energy consumption does not affect income, and as such, energy conservation policies may be pursued without adversely affecting income.

Our Goal

The objective of this document is to examine the causal relationship between **GDP growth** and **energy consumption**, from 5 different countries;
Italy, Germany, Belgium, Sweden, Netherlands.

Finally, also trying to observe what are the effects that a **shock** from one variable could cause to the other.

Data of the project

Data source: **The World Bank – World Development Indicators**

Main variables of our analysis:

- **PGDP**: log of Adjusted net national income per capita (constant 2015 US$)
- **PEC**: log of Energy use (kg of oil equivalent per capita)

Sample time period: Annual data from **(1972 – 2015)**
Sample country: Italy, Germany, Belgium, Sweden, Netherlands.

Idea Concept & methodology

1 Stationarity analysis

- ACF test
- AIC & BIC criterion
- ADF test
- Graphical Rappresentations

2 VAR model

- AIC & BIC criterion
- Creation e interpretation of the VAR model

3 Granger Causality

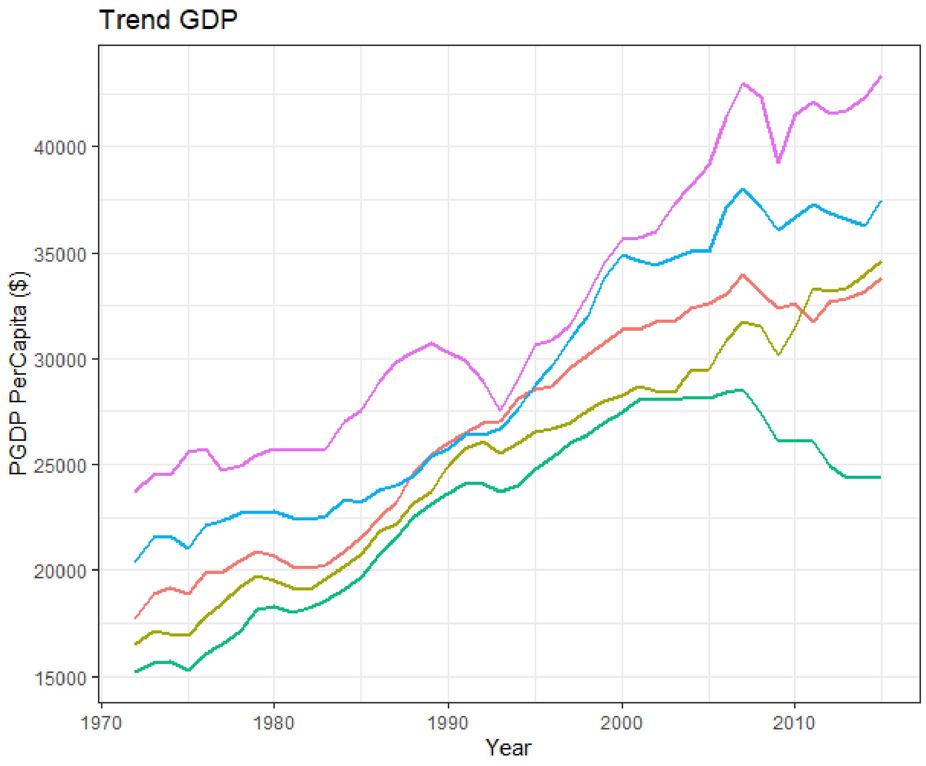
- Evaluations of causality between variables

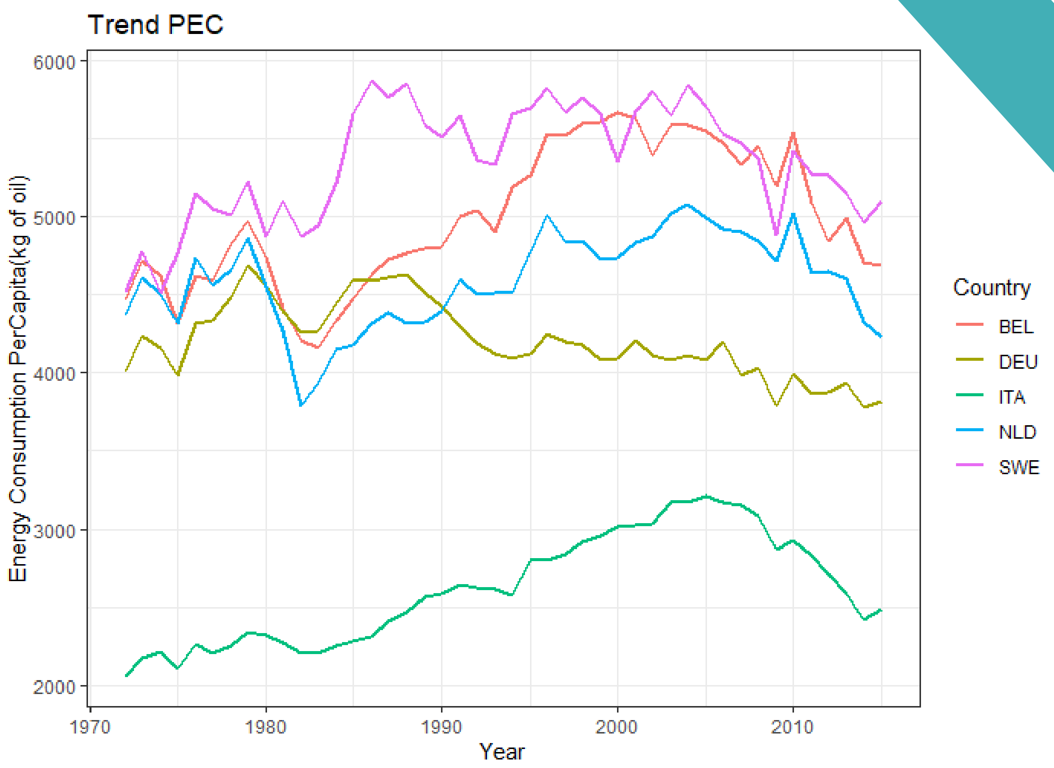
4 Impulse Reponse Function

- Reaction of a variable to another variable's shock

Stationarity analysis

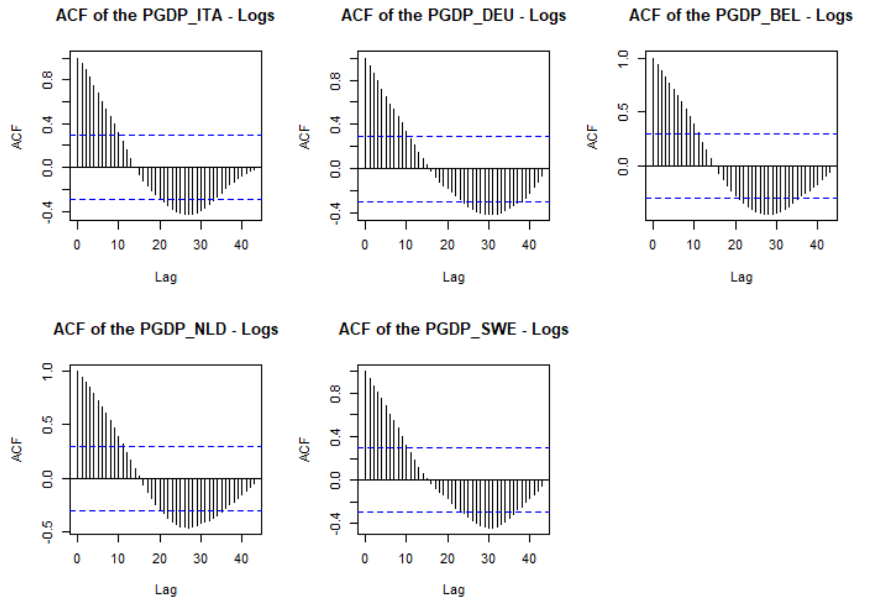
- Raw data



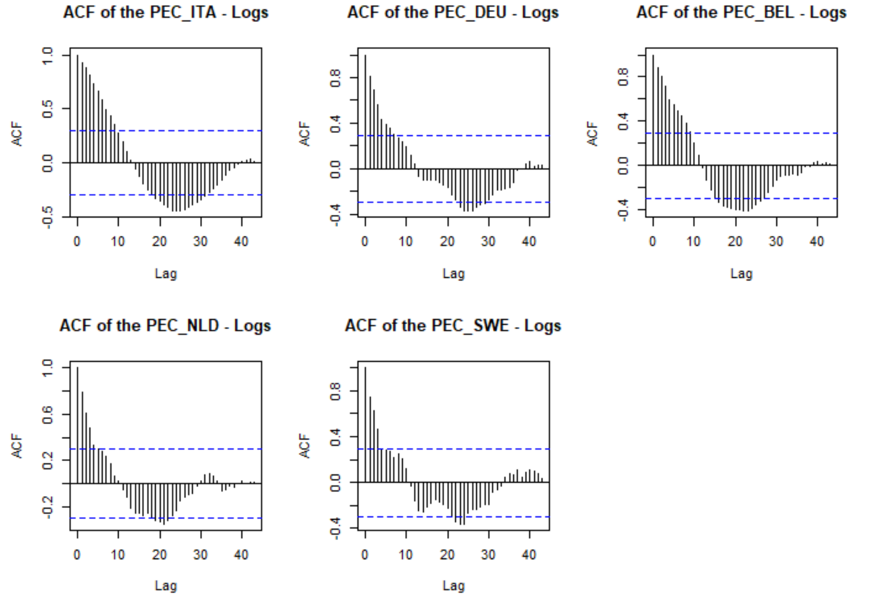


Stationarity analysis

PGDP



PEC



The following graphs represent the **test of the autocorrelation function (ACF)** on the raw data, as can be seen they would seem statistically insignificant, therefore we could state that the graphical trends shown in the previous slide are not stationary.

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Stationarity analysis

To work, analyze and forecast with time series **is necessary to work with stationary data**, so we have to understand how to make these variables stationary, the **first step** is to understand analytically, through the **ADF test**, if they are actually not stationary, the **second step**, if they are not stationary, is to try to verify if their **log-difference** is it, always with **ADF test** and continue the analysis with those. Therefore, using the **AIC and BIC** information criteria, we look for the best number of lags to find the stationarity of both time series.

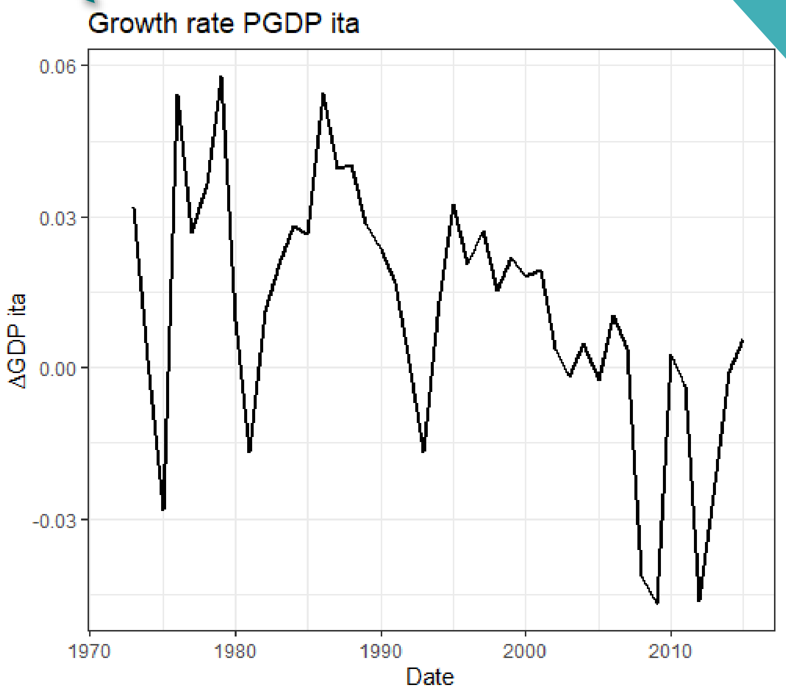
Country	Variable	AIC (1)	AIC (2)	AIC (3)	AIC (4)	BIC (1)	BIC (2)	BIC (3)	BIC (4)	Optimal lag
ITA	PGDP	-198.89	-200.31	-195.38	-198.3	-193.61	-193.36	-186.81	-188.17	AIC (2)
	PEC	-167.92	-162.66	-157.4	-160.5	-162.64	-155.71	-148.83	-150.37	AIC (1)
DEU	PGDP	-201.42	-195.21	-195.14	-188	-196.14	-188.26	-186.57	-177.87	AIC (1)
	PEC	-174.24	-170.57	-163.84	-159.86	-168.96	-163.62	-155.27	-149.72	AIC (1)
BEL	PGDP	-208.91	-205.48	-198.87	-198.34	-203.62	-198.53	-190.31	-188.21	AIC (1)
	PEC	-154.34	-148.95	-142.95	-141.91	-149.05	-142	-134.38	-131.78	AIC (1)
NLD	PGDP	-199.79	-196.63	-190.61	-186.03	-194.51	-189.68	-182.04	-175.89	AIC (1)
	PEC	-149.27	-144.01	-137.8	-133.06	-143.99	-137.06	-129.23	-122.93	AIC (1)
SWE	PGDP	-176.43	-170.87	-166.26	-161.14	-171.15	-163.92	-157.69	-151	AIC (1)
	PEC	-148.16	-143.22	-140.77	-135.83	-142.87	-136.27	-132.2	-125.69	AIC (1)

The **AIC model** is preferred because, as *Stock suggested in an article published in 1994*, the AIC models are more functional when the values to be **compared are negative**, on the contrary it is preferred to use the BIC models.

Stationarity analysis

Once the optimal lag has been calculated, we proceed analytically to verify the stationarity of the variables **with the new lag**, this time in addition to **the raw** data we also use the **First-difference** of both variables. Growth rate: $g_Y = \frac{Y_t - Y_{t-1}}{Y_{t-1}} \approx ln(Y_t) - ln(Y_{t-1}) = \Delta ln(Y_t)$

Country	Variable	Level	First difference
ITA	PGDP	0.496	-3.829**
	PEC	0.709	-3.905**
DEU	PGDP	-2.311	-5.626**
	PEC	-2.456	-4.655**
BEL	PGDP	-0.756	-3.481**
	PEC	-0.899	-4.355**
NLD	PGDP	-1.839	-4.431**
	PEC	-1.86	-4.679**
SWE	PGDP	-2.842*	-4.925**
	PEC	-1.619	-5.828**



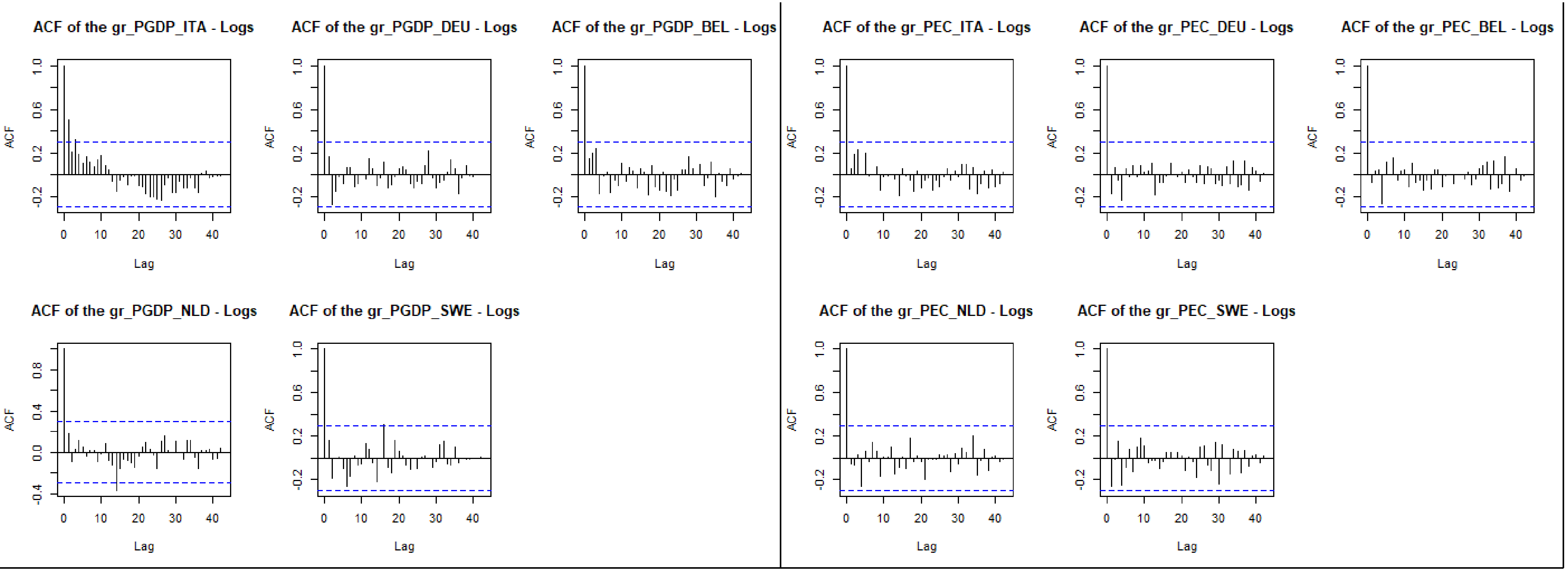
Following the ADF test, we can conclude that the **raw data** (Level) is not stationary, while the **log-difference data** (First difference) is **significantly stationary at the 5% level**.

Augmented Dickey-Fuller Test:

- H_0 => Presence of unit root
- H_1 => stationarity

Stationarity analysis

These are the new graphs of the **ACF test** carried out on **GDP growth** and **PEC growth** data, here too we have a fairly clear confirmation of the **stationarity of these historical series**.



VAR model

Up to now we have seen how to find the stationarity of one time series at a time, with the **VAR model** we can do analyzes and forecasts **jointly with two or more time series**.

Our goal now is therefore to develop a **VAR (Vector Autoregression) model**, to understand the type of relationship that exists between the **growth PGDP** and **growth PEC** in all 5 countries.

To do this, find once again the **AIC and BIC information criteria**, to understand in an analytical way what are the **optimal delays** for developing this model, preferring, for the same reasons given previously, the AIC model.

Country	AIC (1)	AIC (2)	AIC (3)	AIC (4)	BIC (1)	BIC (2)	BIC (3)	BIC (4)	Optimal lag
ITA	-15.36	-15.21	-15.18	-15.04	-15.11	-14.78	-14.58	-14.27	AIC (1)
DEU	-14.83	-14.78	-14.84	-14.76	-14.57	-14.36	-14.25	-13.99	AIC (3)
BEL	-14.71	-14.64	-14.5	-14.66	-14.45	-14.22	-13.9	-13.9	AIC (1)
NLD	-14.09	-13.92	-13.81	-13.79	-13.83	-13.49	-13.21	-13.03	AIC (1)
SWE	-13.43	-13.31	-13.3	-13.16	-13.17	-12.88	-12.7	-12.39	AIC (1)

VAR model

$$\underset{k\times 1}{Y_t} = \underset{k\times 1}{B_0} + \underset{k\times k}{\mathbf{B_1}}\,\underset{k\times 1}{Y_{t-1}} + \cdots + \underset{k\times k}{\mathbf{B_p}}\,\underset{k\times 1}{Y_{t-p}} + \underset{k\times 1}{u_t}$$

which in its extensive form reads (without the costant for sake of simplicity):

$$\begin{pmatrix} Y_{1,t} \\ Y_{2,t} \\ \cdots \\ Y_{k,t} \end{pmatrix} = \begin{pmatrix} \beta^1_{1,1} & \cdots & \beta^1_{1,k} \\ \vdots & \ddots & \vdots \\ \beta^1_{k,1} & \cdots & \beta^1_{k,k} \end{pmatrix} \begin{pmatrix} Y_{1,t-1} \\ Y_{2,t-1} \\ \cdots \\ Y_{k,t-1} \end{pmatrix} + \cdots + \begin{pmatrix} \beta^p_{1,1} & \cdots & \beta^p_{1,k} \\ \vdots & \ddots & \vdots \\ \beta^p_{k,1} & \cdots & \beta^p_{k,k} \end{pmatrix} \begin{pmatrix} Y_{1,t-p} \\ Y_{2,t-p} \\ \cdots \\ Y_{k,t-p} \end{pmatrix} + \begin{pmatrix} u_{1,t} \\ u_{2,t} \\ \cdots \\ u_{k,t} \end{pmatrix}$$

where the upper index β is not the power, but the lag index.

This is the formula and method of building a **VAR model**, we adopt this provision for each of the 5 countries and for each of these, as many delays are used as those indicated in the previous table.

We say that a variable $Y_{1,t}$ is a **Granger-cause** of another variable $Y_{2,t}$, if knowledge of $Y_{1,t}$ helps to better predict $Y_{2,t+j}$ for a $j > 0$.

Providing a **practical example** on a single country, **Italy**, we can write that:

$$Y_1 = \beta_0 + \beta_{1,1} * Y_{1,t-1} + \beta_{2,1} * Y_{2,t-1}$$
$$Y_2 = \beta_0 + \beta_{1,2} * Y_{1,t-1} + \beta_{2,2} * Y_{2,t-1}$$

And to test the presence or not of causality between **PGDP** and **PEC** (Y_1 and Y_2), we do for **PGDP** => **H_0**: $\beta_{2,1} = 0$ *(non-stationarity)*

=> **H_1**: $\beta_{2,1} \neq 0$ *(stationarity)*

Granger Causality

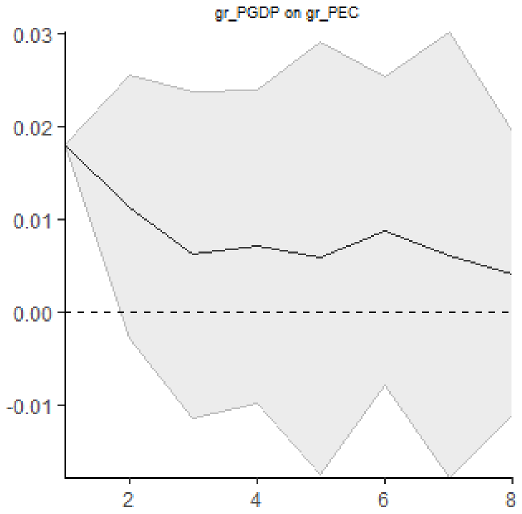
Country	PEC Granger causes PGDP	PGDP Granger causes PEC	Direction of causality
ITA	1.53[0.219]	11.68[0.001]**	PEC=/>PGDP PGDP=>PEC
DEU	0.14[0.934]	1.67[0.183]	PEC=/>PGDP PGDP=/>PEC
BEL	0.34[0.559]	3.17[0.079]*	PEC=/>PGDP PGDP=>PEC
NLD	0.07[0.785]	0[0.952]	PEC=/>PGDP PGDP=/>PEC
SWE	0.12[0.727]	0.06[0.807]	PEC=/>PGDP PGDP=/>PEC

The results presented in the Table provide convincing evidence of a uni-directional causality ranging from **PGDP to PEC** for **Belgium** at the 10% significance level and for **Italy** at the 5% significance level. *This denotes an economy that is less dependent on energy, one in which the implementation of energy-saving policies would have few, if any, negative effects on income*.
In **neither of the other countries** do **PGDP or PEC** enter significantly into each other's equation, *indicative of a lack of causality*.

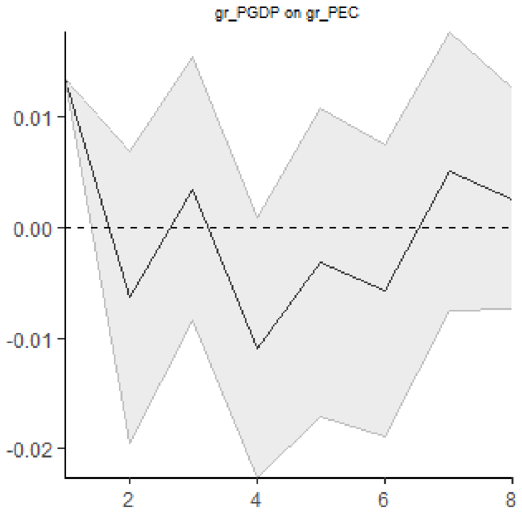
Our results sometimes differ from those of *Chien-Chiang Lee (2006)* who found evidence of uni-directional causality going from PEC to PGDP in **Belgium** and the **Netherlands**, uni-directional causality going from PGDP to PEC in **Italy** as for us and lack of causality in **Germany** and **Sweden** as in us.
The **differences** in the results of this work and those of previous studies could be attributable to the **choice of the sample period**, to the **different combinations of the variables** or to the **differences in the econometric methods**.

Impulse Reponse Functions

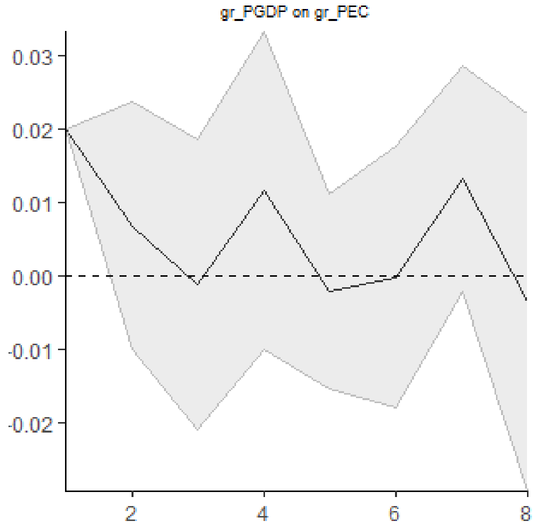
ITALY



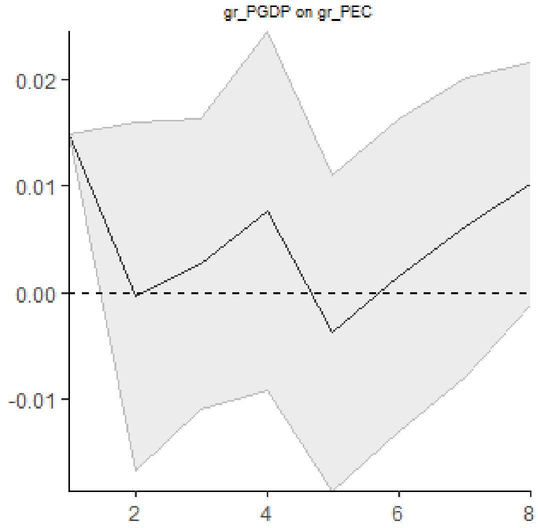
GERMANY



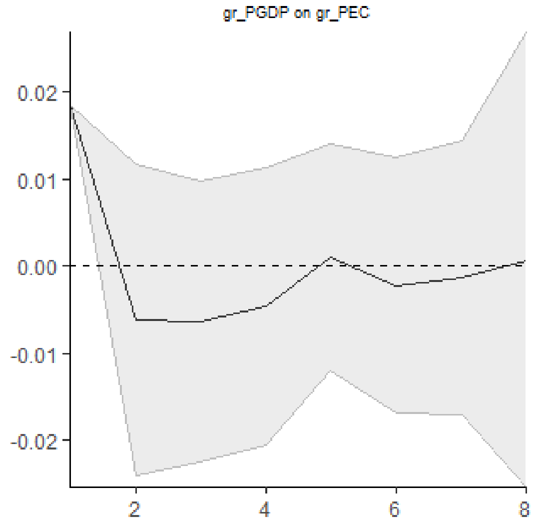
BELGIUM



NETHERLANDS



SWEDEN



In the end, we generated **IRF** *(Impulse Reponse Function)* plot to understand the extent to which a **unit shock** in one variable **influences** the other variables in **subsequent periods**.

We can **conclude** that in all countries the **unit shock** of the **PGDP** has a **significant effect**, more or less high unlike the countries, on the **PEC** only up to the following period, the variations **after the first year are not significant**.

Reference

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- Stock, J.M., 1994. Unit roots, structural break and trends. In: Engle, R.F., McFadden, D. (Eds.). Handbook of Econometrics, North Holland, pp. 2738–2841.