Renewable Energies and Climate Change: How to Ease the Energy Transition?

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Table of contents

Introduction

Motivation

- The growing interest on renewable energy is due to:
  - **reducing greenhouse gas emissions** (*Song, J., Yang, W., & Higano, Y. 2015, Khan, M. T. I., Ali, Q., & Ashfaq, M. 2018*),
  - **reducing energy imports** (*Zhu, Danmei, et al. 2020*),
  - **reducing the use of fossil fuels and carbon dioxide emissions** (*Marques, A. C., Fuinhas, J. A., & Pereira, D. A. 2018, Mostafaeipour, A., Bidokhti, A., Fakhrzad, M. B., Sadegheih, A., & Mehrjerdi, Y. Z. 2022*).
- **Until the 1990s hydropower and wood** were the most used renewable energy resources (*International Energy Agency (IEA)*).
- **Since the 1990s** the amount of energy from **solar**, **wind**, **geothermal** has increased (*IEA, Energy Mix December 2021*).

Aim

- The aim of the study is to provide a framework able to detect the **determinants** that have a **relevant** impact on the renewable energy market across countries.
- Investigate the interactions of the determining factors among countries.
- The benefit for a policymaker is to understand which **factors** and **policies** contribute to easing the renewable energy transition.

Model specification

Matrix AutoRegressive model

- **M**atrix **A**uto**R**egressive model of order p, $MAR(p)$, is an extension of the traditional VAR model (*Chen, Xiao, and Yang, 2020*).
- MAR(1) is defined as:

$$\mathbf{X}_t = \mathbf{A}\mathbf{X}_{t-1}\mathbf{B}^{'} + \mathbf{E}_t \tag{1}$$

Where:

- $\mathbf{X}_t$ is the $m \times n$ matrix observed at time t for $t \in \{1, 2, \ldots, T\}$.
- $\mathbf{A} = (a_{ij})$ and $\mathbf{B} = (b_{ij})$ are $m \times m$ and $n \times n$ autoregressive coefficient matrices.
- $\mathbf{E}_t = (e_{t,ij})$ is a $m \times n$ matrix white noise.

Vectorization

The $MAR(1)$ model can represented in the form of a vector autoregressive model

$$vec(\mathbf{X}_t) = (\mathbf{B} \otimes \mathbf{A}) vec(\mathbf{X}_{t-1}) + vec(\mathbf{E}_t) \qquad (2)$$

where $\otimes$ denotes the matrix Kronecker product.

$\Rightarrow$ it can be viewed as a special case of the classical $VAR(1)$.

Remarks

- $MAR(1)$ requires $m^2 + n^2$ coefficients as the entries of $\mathbf{A}$ and $\mathbf{B}$.
- Unrestricted $VAR(1)$ requires $m^2 n^2$ coefficients.

The Error Matrix sequence $\{\mathbf{E}_t\}$

Properties:

- $\mathbf{E}_t$ and $\mathbf{E}_s$ are not correlated for $t \neq s$.
- The entries of $\mathbf{E}_t$ can be correlated, thus $\Sigma = Cov(vec(\mathbf{E}_t))$ that is a $(mn) \times (mn)$ matrix.
- Structured covariance matrix can be expressed as:

$$Cov(vec(\mathbf{E}_t)) = \Sigma_c \otimes \Sigma_r$$

where Σ_r and Σ_c are $m \times m$ and $n \times n$ symmetric positive definite matrices.

Model Estimation

1. Projection method: considering MAR(1) as a special case of VAR(1), we get the estimators by projecting $\hat{\Phi}$ onto the space of Kronecker products and solving the *nearest Kronecker product* (NKP) problem:

$$(\hat{\mathbf{A}}_1, \hat{\mathbf{B}}_1) = \arg\min_{\mathbf{A},\mathbf{B}} ||\hat{\Phi} - \mathbf{B} \otimes \mathbf{A}||_F^2 \tag{3}$$

where $\hat{\Phi}$ is the MLE of Φ.

2. Iterated least squares: assuming the entries of $\mathbf{E}_t$ are i.i.d. $N(0, \sigma_e)$, the MLE is the solution of the LSE problem for $\mathbf{A}$ and $\mathbf{B}$

$$\min_{\mathbf{A},\mathbf{B}} \sum_t ||\mathbf{X}_t - \mathbf{A}\mathbf{X}_{t-1}\mathbf{B}^{'}||_F^2. \tag{4}$$

The Projection estimators, $\hat{\mathbf{A}}_1$, $\hat{\mathbf{B}}_1$, are the starting point for the **iterative procedure** used for computing the LSE, namely $\hat{\mathbf{A}}_2$, $\hat{\mathbf{B}}_2$.

Model interpretation and oIRF

- The left matrix $\mathbf{A}$ reflects row-wise interactions, and the right matrix $\mathbf{B}'$ introduces column-wise dependence.
- The impulse response function with orthogonal innovation (oIRF) of a unit standard deviation change in $e_{t,ij}$ is

$$\mathbf{F}_{i,j}(k) = (\mathbf{B}^k \otimes \mathbf{A}^k)\, \Sigma[, m(j-1)+i]. \tag{5}$$

Empirical Results

Data

- We study the **G7 European (EU27)** countries: Germany, France and Italy.
- The frequency is **quarterly** and the data span over the period **from 1980 to 2020**.
- **Quarterly GDP** from Organization for Economic Co-operation and Development (OECD).
- **Renewable energy production** and **Climatic factors** from Copernicus Climate Data Storage (CDS).
- **Net fluxes** at the surface, atmospheric mixing ratios at model levels, and column-mean atmospheric mixing ratios for carbon dioxide (CO_2) from the Atmospheric Copernicus Database (CAMS).

Matrix Form

$$
\mathbf{X}_t = \begin{array}{r c}
 & \begin{array}{ccc} DEU & FRA & ITA \end{array} \\
\begin{array}{r} \text{precipitation} \\ \text{GDP} \\ \text{hydropower} \\ \text{wind power} \\ \text{wind speed} \\ \text{solar power} \\ \text{CO}_2 \\ \text{solar rads} \end{array} &
\begin{bmatrix}
x_{p,deu} & x_{p,fra} & x_{p,ita} \\
x_{GDP,deu} & x_{GDP,fra} & x_{GDP,ita} \\
x_{hp,deu} & x_{hp,fra} & x_{hp,ita} \\
x_{wp,deu} & x_{wp,fra} & x_{wp,ita} \\
x_{ws,deu} & x_{ws,fra} & x_{ws,ita} \\
x_{sp,deu} & x_{sp,fra} & x_{sp,ita} \\
x_{CO_2,deu} & x_{CO_2,fra} & x_{CO_2,ita} \\
x_{sr,deu} & x_{sr,fra} & x_{sr,ita}
\end{bmatrix}
\end{array}
$$

Model fitting

Matrix $\hat{\mathbf{A}}$	Precipitation	GDP	Hydro power	Wind power	Wind speed	Solar power	CO_2	Solar radiation
Precipitation	-0.024	-0.047	-0.014	0.238^c	-0.104	-0.0234^c	0.018	0.233^c
GDP	0.064	-0.288^a	-0.081	-0.244	0.107	-0.389^b	0.018	0.499^a
Hydropower	0.224^a	-0.048	0.401^a	0.323^a	-0.304^a	-0.345^a	0.074^a	0.417^a
Wind power	-0.165	0.073	0.030	0.259	-0.187	-0.453	0.039	0.447
Wind speed	-0.171	-0.038	0.035	0.362	-0.271	-0.401	0.021	0.403
Solar power	0.0489	0.085	-0.044	-0.318	0.178	0.211	-0.052	-0.155
CO_2	0.022	0.048	-0.107	-0.137	0.017	-0.111	0.519^a	0.207^c
Solar radiation	0.091	0.093	-0.032	-0.277	0.133	0.199	-0.059	-0.123

Note: *a* - significance level at 1%, *b* - significance level at 5%, *c* - significance at 10%.

Matrix $\hat{\mathbf{B}}$	Germany	France	Italy
Germany	1.060^a	0.005	0.114
France	0.381^a	1.023^a	-0.083
Italy	0.207^b	0.284^a	0.806^a

Note: a, b, c - significance levels.

oIRF - Precipitation

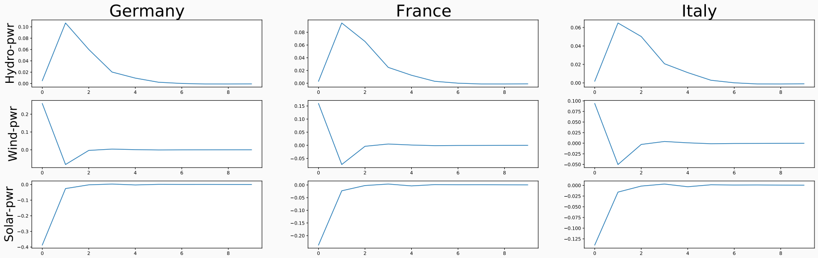

Figure: *oIRFs with a unit st.dev. shock on Germany's Precipitation.*

- **Solar power** production **decreases** [Del Pero et al., 2021].
- **Emissions' reduction** from the second quarter.
- **Increment of hydropower** generation.

<u>**Notice**</u> the effects' magnitude decrease as spatial distance from the shock increases.

Effect of precipitation shock on emissions

The effect of precipitation on CO_2 emissions and solar radiation.

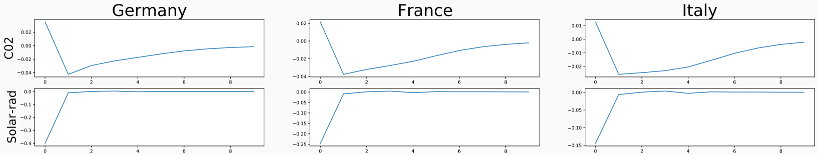

Figure: *oIRFs with a unit st.dev. shock on Germany's Precipitation.*

- The effect of **carbon cycle** [Wigley and Schimel, 2000].

oIRF - GDP

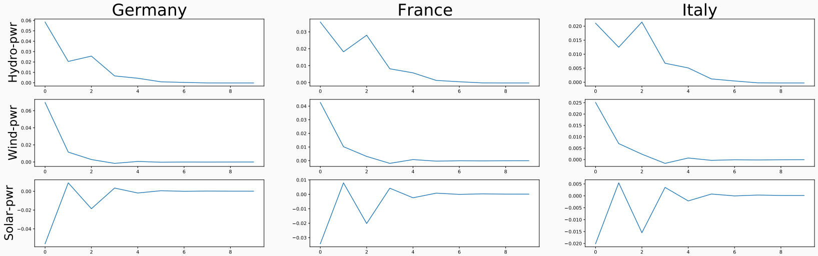

Figure: oIRFs with a unit st.dev. shock on Germany's GDP.

- **Beneficial effect** for **hydropower** generation.
- **Negative** for **solar power** production [Ong et al., 2013].
- **Improved wind power**'s level.

Effect of GDP shock on emissions

The effect of GDP on CO_2 emissions.

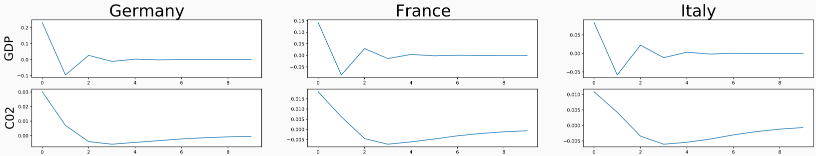

Figure: *oIRFs with a unit st.dev. shock on Germany's GDP.*

- Strong **increase** in **emissions** [Mardani et al., 2019].
- Negative impact of past GDP on itself as **cyclical behavior** and **recovering capacity of economy** [Tiao and Tsay, 1994, Potter, 1995].

Concluding Remarks

Summary

Thanks to its bilinear form, the MAR allows to:

- Study and catch **how different indicators interact among them**, preserving the matrix structure of the multi-evaluated time series.
- Understand **how all the indicators of one country influence and impact those of all other countries**.

$\rightarrow$ The policymaker is provided with a tool that supports **data-driven strategic policies**: *simulate climate change* to decide better *which kind of renewable energy to invest in*.

Thank you for your attention!

Supplemental material

Index

- Shock of a unit st.dev. on Germany's wind speed.
- Shock of a unit st.dev. on Germany's solar radiation.

oIRF - Solar radiation

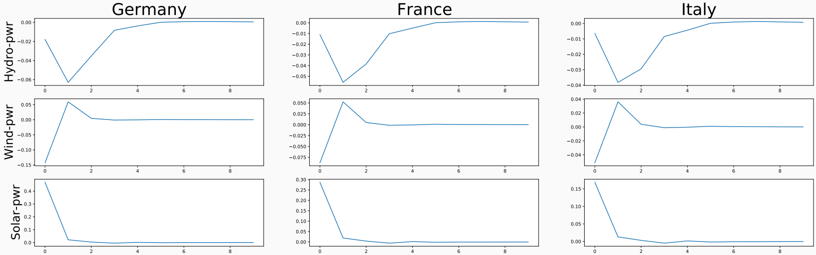

Figure: *oIRFs with a unit st.dev. shock on Germany's solar radiation.*

- Benefit in solar power production.
- Slowdown of hydropower from reservoirs [Gorjian et al., 2021].
- Harmful effect for wind power generation [Letson et al., 2020].
- Increase in emissions' levels.

Effect of solar radiation shock on emissions

The effect of solar radiation on CO_2 emissions.

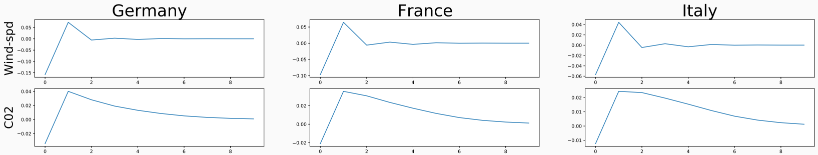

Figure: *oIRFs with a unit st.dev. shock on Germany's solar radiation.*

- The emissions could increase as a consequence of solar radiation induced increase in global carbon uptake of both land and sea [Wigley and Schimel, 2000].

oIRF - Wind speed

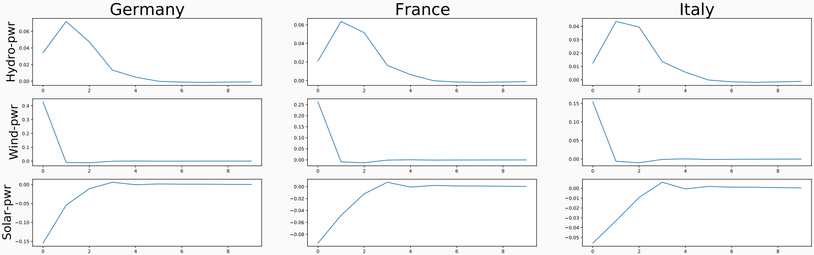

Figure: *oIRFs with a unit st.dev. shock on Germany's wind speed.*

- Benefit in wind power production.
- Increase in hydropower generation [Ávila et al., 2021].
- Harmful effect for solar power possible due to dust settle [Goossens and Van Kerschaever, 1999].
- Decrease of emissions' levels.

Effect of wind speed shock on emissions

The effect of wind speed on CO_2 emissions.

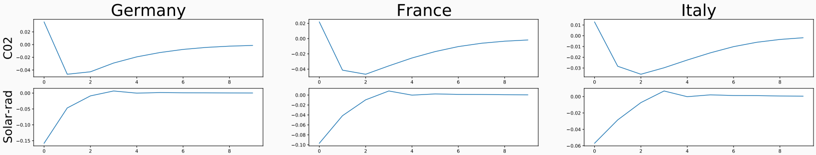

Figure: *oIRFs with a unit st.dev. shock on Germany's wind speed.*

- The emissions could decrease as a consequence of wind speed induced decrease in global carbon uptake of both land and sea [Wanninkhof and Triñanes, 2017].

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