Which factors are contributing to Greenhouse gas emissions in Italy?

Bayesian analysis

David Fernandez, Alessia Leo Folliero

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UNIVERSITÀ DEGLI STUDI DI MILANO

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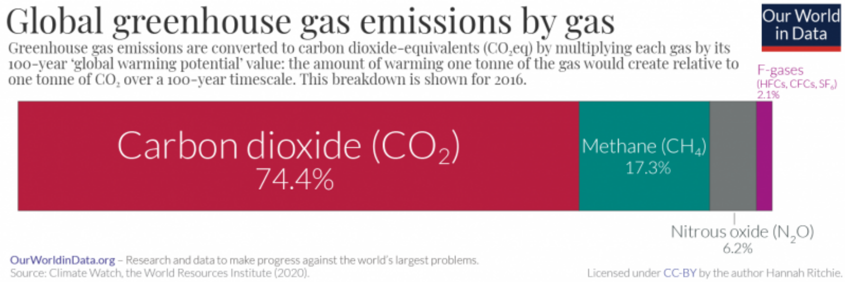
Which factors are contributing to Greenhouse gas emissions in Italy?

What are Greenhouse gases? [1]



[1] *Greenhouse gas emissions:* https://bit.ly/423jXKk

How do they affect the climate? [2]

- increase in temperature
- increased frequency of severe storms
- increases in droughts
- warming rising ocean

[2] *The consequences of the greenhouse effect: from desertification to floods*: https://bit.ly/40QZcjq

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2 Data description

Data

2 Data description

- T = 30, from 1990 to 2020
- Frequency: yearly
- 19 variables, including *net greenhouse gas emissions per capita*
- Variables scaled and transformed in first differences

Data

Features	Unit of measure
Net greenhouse gas emissions	tonnes per capita
Environmental taxes	percentage of GDP
GDP pc	Constant 2010 US dollars
Industrial production	Index 2015=100
Energy imp dep	percentage
Naturalgas imports	Million m^3
Oil imports	Thousand tonnes
Total energy supply	Gigawatt-hour
Gross electricity production	Gigawatt-hour
Share of land under permanent crops	percentage

Features	Unit of measure
Area harvested Rice	Area ha
Fertilizer used per area of cropland	kg per ha
Share in land area Forest Land	percentage
Rail tracks KM	km
Length of motorways	km
Number of motorcycle	Units
Total freight loaded and unloaded	tonnes
Livestock heads	Thousand heads
RES capacity	Megawatt

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3 Theoretical framework

Model specification

The VAR(p) for Y_t is defined as (Canova and Ciccarelli, 2013):

$$Y_t = A_0 + A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + e_t \quad e_t \sim N(0, \Sigma) \tag{1}$$

The Likelihood function of a VAR(p) model can be decomposed (Canova, 2007) into the product of a Normal density for β and a Wishart density for Σ^{-1}:

$$\mathcal{L}(y|\beta, \Sigma) \propto \mathbb{N}(\beta|\beta_{ols}, \Sigma, X, Y) \text{ x } \mathbb{W}(\Sigma^{-1}|Y, X, \beta_{ols}, df) \tag{2}$$

Our prior for the vector of coefficients β is $\{\beta|y_1,...,y_n,\Sigma\}\sim$ multivariate normal(μ_n,Λ_n), describing a conditional posterior density:

$$\begin{aligned}\pi(\beta|\Sigma,y)\propto exp\{-0.5(y-X\beta)^{'}(I_T\otimes\Sigma^{-1})(y-X\beta)\}\\ \cdot exp\{-0.5(\beta-\mu_\beta)^{'}V_\beta^{-1}(\beta-\mu_\beta)\}\ \sim N(A,B)\end{aligned}\tag{3}$$

where $B = V_\beta^{-1}+X^{'}(I_T\otimes\Sigma^{-1})X$, and $A = B^{-1}(V_\beta^{-1}\beta_0+X^{'}(I_T\otimes\Sigma^{-1})y)$, μ_β is the mean over β and V_β the variance

Prior and posterior densities for Σ^{-1}

Our prior for the matrix of variance covariance of errors $\{\Sigma^{-1}$ is $\Sigma|y_1, ..., y_n, \beta\} \sim$ inverse-Wishart(ν_n, S_n^{-1}),describing a conditional posterior density:

$$\begin{aligned}\pi(\Sigma|\beta, y) &\propto |\Sigma|^{\frac{-\nu_0+T+n+1}{2}} \cdot exp\{-0.5 \cdot tr(S_0\Sigma^{-1}\} \\ &\cdot exp\{-0.5 \cdot tr(\sum_{t=1}^{T}(y_t - X_t\beta)^{'}(y_t - X_t\beta)\Sigma^{-1})\} \\ &\sim iW(\nu_0 + T, S_0 + \Sigma(y_t - X_t\beta)(y_t - X_t\beta)^{'})\end{aligned} \tag{4}$$

Gibbs sampler steps

1. sample $\beta^{(s+1)}$ from its full conditional density:
   1.1 compute A and B from $y_1, \dots, y_n$ and $\Sigma^{(0)}$ using OLS;
   1.2 sample $\beta^{(s+1)} \sim$ multivariate normal(A, B).
2. sample $\Sigma^{(s+1)}$ from its full conditional distribution:
   2.1 compute S_n from $y_1, \dots, y_T$ and $\beta^{(s+1)}$;
   2.2 sample $\Sigma^{(s+1)} \sim$ inverse-Wishart$(\nu_0 + T, S_0 + \Sigma(y_t - X_t\beta^{(s+1)})(y_t - X_t\beta^{(s+1)})')$

Number of iterations are set to 20,000 with a burn-in of 2,000

Gibbs sampler, prior beliefs

1. $\beta_0 = \beta_{OLS}$
2. $V_{\beta}^{-1} = I_T$
3. $\Sigma^{-1} = \Sigma_{OLS}^{-1}$
4. $\nu_0 = 2 * n$
5. $S_0 = T_T$

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Models specifications

4 Models and results

Models lags were selected by applying the Schwartz Information Criterion to the different subsets of data described All models are VAR(1), described in the following table:

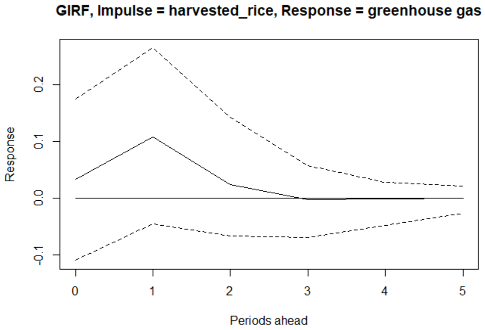
	y_t^1	y_t^2	y_t^3
Model 1	Greenhouse gas	Harvested rice	Permanent crops
Model 2	Greenhouse gas	Energy imports dependency	Oil imports
Model 3	Greenhouse gas	GDP per capita	Fertilizer

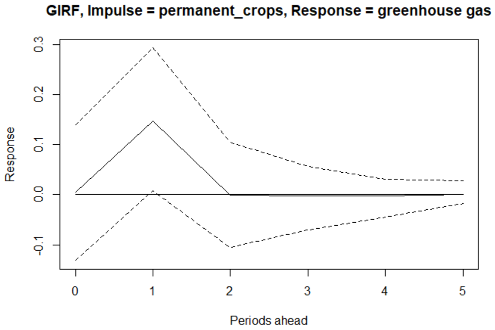
Model 1 $\hat{\beta}$ and $\hat{\Sigma}$

Model 1 $\hat{\beta}$	$greenhouse_{t-1}$		$rice_{t-1}$		$crops_{t-1}$		$const$	
	$\hat{\beta}_{ols}$	$\hat{\beta}_B$	$\hat{\beta}_{ols}$	$\hat{\beta}_B$	$\hat{\beta}_{ols}$	$\hat{\beta}_B$	$\hat{\beta}_{ols}$	$\hat{\beta}_B$
$greenhouse_t$	0.14	0.14	0.08	0.08	0.14	0.14	-0.08	-0.08
$rice_t$	-0.99	-0.99	0.21	0.21	0.04	0.04	-0.01	-0.01
$crops_t$	-0.38	-0.38	0.03	0.02	-0.20	-0.20	-0.01	-0.01

Model 1 $\hat{\Sigma}$	$greenhouse_{t-1}$		$rice_{t-1}$		$crops_{t-1}$	
	$\hat{\Sigma}_{ols}$	$\hat{\Sigma}_B$	$\hat{\Sigma}_{ols}$	$\hat{\Sigma}_B$	$\hat{\Sigma}_{ols}$	$\hat{\Sigma}_B$
$greenhouse_{t-1}$	0.07	0.11	0.03	0.02	0.00	0.00
$rice_{t-1}$	0.03	0.02	0.71	0.69	0.12	0.11
$crops_{t-1}$	0.00	0.00	0.12	0.11	0.82	0.79

GIRF, Model 1


GIRF, Impulse = harvested_rice, Response = greenhouse gas
Response
0.2
0.1
0.0
-0.1
0
1
2
3
4
5
Periods ahead


GIRF, Impulse = permanent_crops, Response = greenhouse gas
Response
0.3
0.2
0.1
0.0
-0.1
0
1
2
3
4
5
Periods ahead

Model 2 $\hat{\beta}$ and $\hat{\Sigma}$

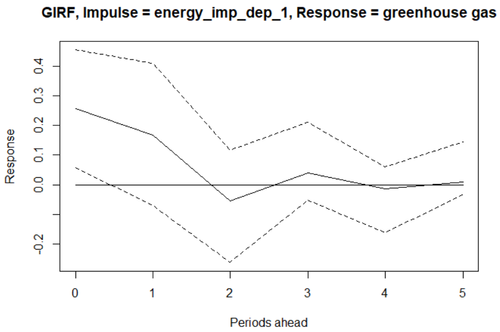
4 Models and results

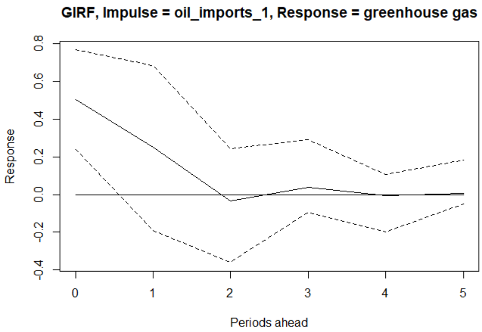
Model 2 $\hat{\beta}$	$greenhouse_{t-1}$		$energy\_dep_{t-1}$		$oil\_imports_1$		$const$	
	$\hat{\beta}_{ols}$	$\hat{\beta}_B$	$\hat{\beta}_{ols}$	$\hat{\beta}_B$	$\hat{\beta}_{ols}$	$\hat{\beta}_B$	$\hat{\beta}_{ols}$	$\hat{\beta}_B$
$greenhouse_t$	-0.06	-0.06	0.12	0.12	0.19	0.20	-0.07	-0.07
$energy\_dep_t$	0.14	0.14	-0.51	-0.51	-0.02	-0.02	-0.12	-0.12
$oil\_imports_t$	0.01	0.01	-0.02	-0.02	-0.04	-0.04	-0.10	-0.10

Model 2 $\hat{\Sigma}$	$greenhouse_{t-1}$		$energy\_dep_{t-1}$		$oil\_imports_1$	
	$\hat{\Sigma}_{ols}$	$\hat{\Sigma}_B$	$\hat{\Sigma}_{ols}$	$\hat{\Sigma}_B$	$\hat{\Sigma}_{ols}$	$\hat{\Sigma}_B$
$greenhouse_{t-1}$	0.09	0.12	0.09	0.08	0.09	0.08
$energy\_dep_{t-1}$	0.09	0.08	0.33	0.33	0.12	0.11
$oil\_imports_{t-1}$	0.09	0.08	0.12	0.11	0.13	0.16

GIRF, Model 2

4 Models and results





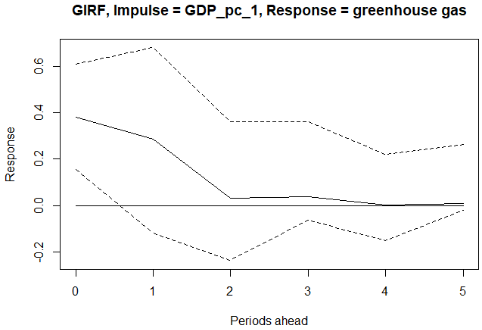
Model 3 $\hat{\beta}$ and $\hat{\Sigma}$

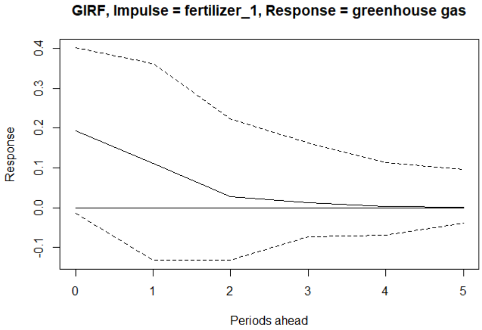
4 Models and results

Model3 $\hat{\beta}$	$greenhouse_{t-1}$		GDP_{t-1}		$fertilizer_{t-1}$		$const$	
	$\hat{\beta}_{ols}$	$\hat{\beta}_B$	$\hat{\beta}_{ols}$	$\hat{\beta}_B$	$\hat{\beta}_{ols}$	$\hat{\beta}_B$	$\hat{\beta}_{ols}$	$\hat{\beta}_B$
$greenhouse_t$	-0.25	-0.18	0.39	0.33	0.10	0.10	-0.13	-0.12
GDP_t	0.17	0.19	0.17	0.14	0.01	0.01	0.03	0.03
$fertilizer_t$	-0.52	-0.35	-0.29	0.17	0.35	0.31	-0.11	-0.09

Model 3 $\hat{\Sigma}$	$greenhouse_{t-1}$		GDP_{t-1}		$fertilizer_{t-1}$	
	$\hat{\Sigma}_{ols}$	$\hat{\Sigma}_B$	$\hat{\Sigma}_{ols}$	$\hat{\Sigma}_B$	$\hat{\Sigma}_{ols}$	$\hat{\Sigma}_B$
$greenhouse_{t-1}$	0.09	0.12	0.09	0.08	0.07	0.06
GDP_{t-1}	0.09	0.08	0.20	0.22	0.06	0.05
$fertilizer_{t-1}$	0.07	0.06	0.06	0.05	0.32	0.33

GIRF, Model 3
4 Models and results



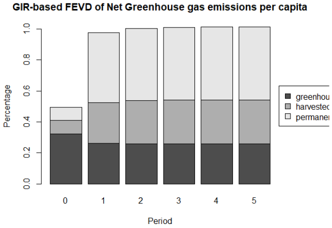


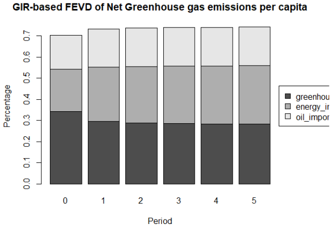
GIRF summary

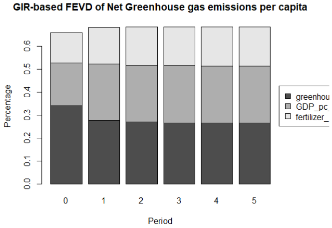
4 Models and results

Models	M1		M2		M3	
n-ahead	rice	crops	ener imp	oil imp	gdp pc	fertilizer
0	0.03	0.01	0.26	0.51	0.38	0.19
1	0.11	0.15	0.17	0.25	0.29	0.11
2	-0.02	0.00	-0.05	-0.03	0.03	0.03
3	0.00	0.00	0.04	0.04	0.04	0.01
4	0.00	0.00	-0.01	-0.01	0.00	0.00
5	0.00	0.00	0.01	0.01	0.01	0.00

FEVD summary







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5 Conclusions

Conclusions and further improvements

- OLS and Bayesian estimate were practically the same
- all the modelled variables have a positive increase in greenhouse gases emissions
- *oil imports*, *GDP pc* and *energy dependency* are the variables with the higher impact on greenhouse gases emissions
- a larger VAR model including all the variables here tested could provide further insights

Thanks!