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The CO2 emissions in Finland, Norway and Sweden: a dynamic relationship.

Abstract

In this paper a dynamic relationship between the CO2 emissions in Finland, Norway and Sweden is presented. With the help of a VAR(2) model, and using the Granger terminology, it is shown that the emissions in Finland are affecting those in Norway and Sweden. Other aspects of this dynamic relationship are presented as well.

Keywords

CO2 emissions, VAR models, Granger causality, impulse response functions, forecast error variance decomposition; software: R, MTS, RATS.

JEL Classification: C01, C10, C32, C50, C88, P18.

Introduction

In this paper we consider the CO2 emissions in Norway, Sweden and Finland, three countries in the Nord of Europe.

The CO2 emissions is a subject of concern for governements in Europe and the rest of the World due to its influence in the climate change. The Conference of Paris 2015 has established clear goals to slow the deterioration of the World Climate.

The selection of the three Nordic states for our analysis is due to the fact that they are three developed economies, that have also signed the Paris 2015 Agreement, and due to their location in the North of Europe, the three countries are facing similar problems in order to fulfill the Paris Agreement.

To get a first view of the situation, we represent in figure 1, the 55 years evolution of the CO2 emissions of the three countries:

Figure 1. CO2 emissions in Finland, Norway and Sweden: 1960-2014

The picture reflects the efforts of Finland, Norway and Sweden for reducing the CO2 emissions in their economies.
The data

The annual data are taken from the World Bank data base. The observations go from 1960 to 2014, and are measured in kilotonnes, kt, of CO2.

The basic statistics for these series are in table 1

| Series     | Obs | Mean             | Std Error       | Minimum     | Maximum     |
|------------|-----|------------------|-----------------|-------------|-------------|
| FINCO2     | 55  | 47859.0837636    | 13232.4507952   | 14939.3580000 | 69130.2840000 |
| NORCO2     | 55  | 35406.6851636    | 11584.5387432   | 13102.1900000 | 60105.7970000 |
| SWEDCO2    | 55  | 61351.4435636    | 13891.4215466   | 43065.2480000 | 92379.0640000 |

Table 1. Basic statistics of the sample

The figures for the CO2 emissions for the years 2009 to 2014, the last year reported in the World Bank data base, are in table 2:

| ENTRY      | FINCO2       | NORCO2       | SWEDCO2      |
|------------|--------------|--------------|--------------|
| 2009:01    | 53149.498    | 55346.031    | 43065.248    |
| 2010:01    | 62082.310    | 60105.797    | 52023.729    |
| 2011:01    | 56816.498    | 45195.775    | 51734.036    |
| 2012:01    | 49134.133    | 49889.535    | 47047.610    |
| 2013:01    | 47219.959    | 58162.287    | 44847.410    |
| 2014:01    | 47300.633    | 47626.996    | 43420.947    |

Table 2. The data for years 2009 to 2014

It is surprising the similarities of these series in the year 2014.

VAR(p) models.

In our study we use the Vector Autoregressive Model of order p: VAR(p). In words of Ruey S. Tsay, *The most used multivariate time series model is the vector autoregressive (VAR) model*, cfr. Tsay, *Multivariate Time Series Analysis*, p. 27, and the author enumerates the computing advantages, as well as the objectives of the multivariate analysis: to study dynamic relationships between variables, as well as to improve the accuracy of predictions, cf., *op.cit.*, p. 1.

In order to introduce the VAR models, let us present its formulation. In our case, we have the vector of series:

\[
\begin{bmatrix}
    \text{finCO2} \\
    \text{norCO2} \\
    \text{swedCO2}
\end{bmatrix}
\]

For simplicity, let us use:

\[
\begin{bmatrix}
    z_t \\
    z_{t-1} \\
    z_{t-2}
\end{bmatrix}
\]

(The reason for this ordering is alphabetical.)

After some exploratory analysis, the VAR appropriate for our case is a VAR(2) model. In symbols,

\[
z_t = \phi_0 + \phi_1 z_{t-1} + \phi_2 z_{t-2} + \alpha_t
\]
With \( a_t \) as a sequence of independent and identically distributed (iid) random vectors, with mean zero and covariance matrix \( \Sigma_a \) which is positive-definite.

In a more explicit form, we have,

\[
\begin{bmatrix}
  z_{1t} \\
  z_{2t} \\
  z_{3t}
\end{bmatrix} =
\begin{bmatrix}
  \phi_{10} \\
  \phi_{20} \\
  \phi_{30}
\end{bmatrix} 
+ \begin{bmatrix}
  \phi_{111} & \phi_{112} & \phi_{113} \\
  \phi_{211} & \phi_{212} & \phi_{213} \\
  \phi_{311} & \phi_{312} & \phi_{313}
\end{bmatrix}
\begin{bmatrix}
  z_{1,t-1} \\
  z_{2,t-1} \\
  z_{3,t-1}
\end{bmatrix} 
+ \begin{bmatrix}
  \phi_{121} & \phi_{122} & \phi_{123} \\
  \phi_{221} & \phi_{222} & \phi_{223} \\
  \phi_{321} & \phi_{322} & \phi_{323}
\end{bmatrix}
\begin{bmatrix}
  z_{1,t-2} \\
  z_{2,t-2} \\
  z_{3,t-2}
\end{bmatrix} 
+ \begin{bmatrix}
  a_{1t} \\
  a_{2t} \\
  a_{3t}
\end{bmatrix}
\]

The coefficients of matrices \( \phi_1 \) and \( \phi_2 \) allow us to relate our model with the Granger causality point of view.

Using the package MTS in R, we get the estimated model:

m2 = VAR(zt,2)

Constant term:
Estimates: 6343.253 3294.181 16508.21
Std.Error: 5084.118 4542.016 4401.756
AR coefficient matrix
AR(1)-matrix

\[
\begin{bmatrix}
  [1,] & [2,] & [3,] \\
  [1,] & 0.7822 & 0.0407 & 0.07467 \\
  [2,] & -0.1437 & 0.4993 & 0.00432 \\
  [3,] & 0.0974 & -0.0450 & 0.68347
\end{bmatrix}
\]

standard error

\[
\begin{bmatrix}
  [1,] & [2,] & [3,] \\
  [1,] & 0.160 & 0.153 & 0.174 \\
  [2,] & 0.143 & 0.137 & 0.156 \\
  [3,] & 0.138 & 0.133 & 0.151
\end{bmatrix}
\]

AR(2)-matrix

\[
\begin{bmatrix}
  [1,] & [2,] & [3,] \\
  [1,] & 0.0665 & -0.0163 & -0.0623 \\
  [2,] & 0.3202 & 0.2136 & -0.0142 \\
  [3,] & -0.2427 & -0.0318 & 0.2031
\end{bmatrix}
\]

standard error

\[
\begin{bmatrix}
  [1,] & [2,] & [3,] \\
  [1,] & 0.166 & 0.164 & 0.166 \\
  [2,] & 0.149 & 0.147 & 0.149 \\
  [3,] & 0.144 & 0.142 & 0.144
\end{bmatrix}
\]

Residuals cov-mtx:

\[
\begin{bmatrix}
  [1,] & [2,] & [3,] \\
  [1,] & 20351832 & 1927911 & 7295705 \\
  [2,] & 1927911 & 16243125 & 1865395 \\
  [3,] & 7295705 & 1865395 & 15255420
\end{bmatrix}
\]

det(SSE) = 4.103473e+21
AIC = 50.42067
BIC = 51.07761
HQ = 50.67471
The residuals of this model validate the model, however some of the coefficients are non-significant at the usual $\alpha = 0.05$. Supressing together these insignificant coefficients, we get the simplified model:

$$m3 = \text{VARchi}(zt, p=2, \text{thres}=1.96)$$
Number of targeted parameters: 16
Chi-square test and p-value: 27.01784 0.04128532

$$> m4 = \text{refVAR}(m2, \text{thres}=1.96)$$

Constant term:
Estimates: 7579.741 0 14517.27
Std.Error: 2528.822 0 3907.614

AR coefficient matrix
AR(1)-matrix

$$\begin{bmatrix}
[1,] & 0.856 & 0.000 & 0.000 \\
[2,] & 0.000 & 0.661 & 0.000 \\
[3,] & 0.000 & 0.000 & 0.901
\end{bmatrix}$$

standard error

$$\begin{bmatrix}
[1,] & 0.0505 & 0.0000 & 0.0000 \\
[2,] & 0.0000 & 0.0856 & 0.0000 \\
[3,] & 0.0000 & 0.0000 & 0.0433
\end{bmatrix}$$

AR(2)-matrix

$$\begin{bmatrix}
[1,] & 0.000 & 0 & 0 \\
[2,] & 0.263 & 0 & 0 \\
[3,] & -0.177 & 0 & 0
\end{bmatrix}$$

standard error

$$\begin{bmatrix}
[1,] & 0.0000 & 0 & 0 \\
[2,] & 0.0643 & 0 & 0 \\
[3,] & 0.0444 & 0 & 0
\end{bmatrix}$$

Residuals cov-mtx:

$$\begin{bmatrix}
[1,] & 20508305 & 1929612 & 7010868 \\
[2,] & 1929612 & 17750860 & 1742123 \\
[3,] & 7010868 & 1742123 & 16107847
\end{bmatrix}$$

det(SSE) = 4.916324e+21
AIC = 50.12867
BIC = 50.31115
HQ  = 50.19923

That is:

$$\begin{bmatrix}
z_t \\ z_{t+1} \\ z_{t+2}
\end{bmatrix} = \begin{bmatrix}
7579.7 \\ 0.000 \\ 14517.3
\end{bmatrix} + \begin{bmatrix}
0.856 & 0.000 & 0.000 \\
0.000 & 0.661 & 0.000 \\
0.000 & 0.000 & 0.901
\end{bmatrix} \begin{bmatrix}
z_{t-1} \\ z_{t-2} \\ z_{t-3}
\end{bmatrix} + \begin{bmatrix}
0.0 & 0.0 & 0.0 \\
0.0 & 0.263 & 0.0 \\
-0.18 & 0.0 & 0.0
\end{bmatrix} \begin{bmatrix}
z_{t-3} \\ z_{t-2} \\ z_{t-1}
\end{bmatrix} + \begin{bmatrix}
\hat{a}_t \\ \hat{a}_{t+1} \\ \hat{a}_{t+2}
\end{bmatrix}$$
Therefore the models of CO2 emissions in each of the three countries can be written as:

For Finland,
\[ z_{1t} = 7579.7 + 0.856z_{1,t-1} + \hat{a}_{1t} \]

For Norway,
\[ z_{2t} = 0.661z_{2,t-1} + 0.263z_{1,t-2} + \hat{a}_{2t} \]

For Sweden,
\[ z_{3t} = 14517.3 + 0.901z_{1,t-1} - 0.18z_{1,t-2} + \hat{a}_{3t} \]

In front of these results, and using *Granger causality* terminology, it seems that CO2 emissions in Finland are causing, are affecting, the CO2 emissions in Norway and Sweden. In other words, it is seen that the Finnish series of CO2 emissions has information helping to characterize future values of the other two series. Cfr. Granger and Newbold, *Forecasting Economic Time Series*, p. 221.

**Impulse response functions**

The VAR formulation of models allow us to establish dynamic relationships between the variables of the system, but at the same time, it is possible to consider this relationship from other points of view. That is: the impulse response and the forecast error variance decomposition.

With the impulse response function it is possible to evaluate the effects of inducing a shock or unitary impulse in one of the variables on its own evolution and on the evolution of the other variables of the system.

The effect is better understood in the MA versión of the VAR model.

\[ z_i = \mu + a_i + \theta_1 a_{i-1} + \theta_2 a_{i-2} + \cdots \]

truncated at some lag \( q \), with \( \theta_0 = 1 \). In compact form, we have:

\[ z_i = \mu + \sum_{i=0}^{q} \theta_i a_{i-i} \]

If we induce a shock or unitary impulse, then, by successive substitutions, we get:

\[ z_i - \mu = \theta_i \]
\[ \vdots \]
\[ z_{i-k-1} - \mu = \theta_{i-k-1} \]
\[ z_{i-k} - \mu = \theta_{i-k} \]
This series of $\theta_i$ are the coefficients of the impulse response in $z_t$ of the unitary shock induced in $a_t$.

If $\Sigma_a$ is not diagonal, it is unrealistic to consider that a unitary shock induced in the error term of one of the variables in the VAR system can be isolated from the other term errors. That is, it would be impossible to establish the impact of a unitary shock in the model of Finland in the model of Norway and in the model of Sweden. The solution to this problem can be found using the Cholesky decomposition of matrix $\Sigma_a$ given the fact that our matrix is positive definite. In this case, there is a matrix $P$, such that $\Sigma_a = PP'$ and $P^t\Sigma_a P^{-1} = I$. With this matrix $P^{-1}$ it is possible to convert $a_t$ on a vector of uncorrelated errors $e_t$, that is:

$$z_t = \mu + \sum_{i=0}^{q} \theta_i P P^{-1} a_{t-i} = \mu + \sum_{i=0}^{q} B_i e_{t-i}$$

After substituting $B_i = \theta_i P$ and $e_{t-i} = P^{-1} a_{t-i}$. The elements of $B_i$ are the impulse response function of $z_t$ with orthogonal innovations.

There is a problem involved with Cholesky decomposition of $\Sigma_a$, worth of mentioning. That is, the order of variables in the vector $z_t$ has consequences, however this is not the place for more details, and we could consider this artificiality as the cost for clarifying the impulse response of the system to the new uncorrelated $e_t$.

Coming to our case, and using the software RATS, the impulse responses, ten steps ahead, for Finland, Norway and Sweden are, in tables 3, 4, and 5.

| Entry | FINCO2 | NORCO2 | SWEDCO2 |
|-------|--------|--------|---------|
| 1     | 4528.60958 | 426.09377 | 1548.1281 |
| 2     | 3877.71039 | 281.55940 | 1395.0090 |
| 3     | 3320.36525 | 1378.64916 | 453.5253 |
| 4     | 2843.12759 | 1932.18491 | -279.3513 |
| 5     | 2434.48353 | 2151.18165 | -840.8525 |
| 6     | 2084.57406 | 2170.21375 | -1262.1419 |
| 7     | 1784.95725 | 2075.17471 | -1569.2577 |
| 8     | 1528.40451 | 1920.22596 | -1783.9137 |
| 9     | 1308.72621 | 1738.93379 | -1924.1781 |
| 10    | 1120.62237 | 1551.57488 | -2005.0494 |

Table 3. Responses to shock in Finland emissions model

| Entry | FINCO2   | NORCO2   | SWEDCO2  |
|-------|----------|----------|----------|
| 1     | 0.00000  | 4191.57536 | 258.2502 |
| 2     | 0.00000  | 2769.75997 | 232.7078 |
| 3     | 0.00000  | 1830.23557 | 209.6916 |
Table 4. Responses to shock in Norway emissions model

| Entry | FINCO2 | NORCO2 | SWEDCO2 |
|-------|--------|--------|---------|
| 1     | 0.00000| 0.00000| 3693.8399|
| 2     | 0.00000| 0.00000| 3328.4971|
| 3     | 0.00000| 0.00000| 2999.2888|
| 4     | 0.00000| 0.00000| 2702.6412|
| 5     | 0.00000| 0.00000| 2435.3338|
| 6     | 0.00000| 0.00000| 2194.4648|
| 7     | 0.00000| 0.00000| 1977.4191|
| 8     | 0.00000| 0.00000| 1781.8405|
| 9     | 0.00000| 0.00000| 1605.6058|
| 10    | 0.00000| 0.00000| 1446.8018|

Table 5. Responses to shock in Sweden emissions model

The graphic representation of these responses are represented in figures 3, 4 and 5

Figure 3. Representation of responses of shock in Finland emissions model

Figure 4. Representation of responses of shock in Norway emissions model
These figures are in agreement with the three estimated models.

The forecast error variance decomposition

The point estimate of the impulse response function cannot reveal the whole consequences of the unitary shock induced. As a help to evaluate more exactly this effect, we have the forecast error variance decomposition. Now it is possible to assign the fraction of variance error due to each of the variables: tables 6, 7, and 8.

In our case, with software RATS, we get:

![Decomposition of Variance for Series FINCO2](chart1)

| Step | Std Error  | FINCO2 | NORCO2 | SWEDCO2 |
|------|------------|--------|--------|---------|
| 1    | 4528.60958 | 100.000| 0.000  | 0.000   |
| 2    | 5961.95795 | 100.000| 0.000  | 0.000   |
| 3    | 6824.20457 | 100.000| 0.000  | 0.000   |
| 4    | 7392.77638 | 100.000| 0.000  | 0.000   |
| 5    | 7783.30602 | 100.000| 0.000  | 0.000   |
| 6    | 8057.62382 | 100.000| 0.000  | 0.000   |
| 7    | 8252.96153 | 100.000| 0.000  | 0.000   |
| 8    | 8393.29461 | 100.000| 0.000  | 0.000   |
| 9    | 8494.71357 | 100.000| 0.000  | 0.000   |
| 10   | 8568.31098 | 100.000| 0.000  | 0.000   |

Table 6. Error variance decomposition for Finland emissions

![Decomposition of Variance for Series NORCO2](chart2)

| Step | Std Error  | FINCO2 | NORCO2 | SWEDCO2 |
|------|------------|--------|--------|---------|
| 1    | 4213.17694 | 1.023  | 98.977 | 0.000   |
| 2    | 5049.92138 | 1.023  | 98.977 | 0.000   |
| 3    | 5545.46136 | 7.029  | 92.971 | 0.000   |
| 4    | 5995.67688 | 16.398 | 83.602 | 0.000   |
| 5    | 6419.84339 | 25.531 | 74.469 | 0.000   |
| 6    | 6797.28532 | 32.968 | 67.032 | 0.000   |
| 7    | 7115.56081 | 38.590 | 61.410 | 0.000   |
| 8    | 7373.71297 | 42.717 | 57.283 | 0.000   |
| 9    | 7577.51608 | 45.716 | 54.284 | 0.000   |
| 10   | 7735.39086 | 47.893 | 52.107 | 0.000   |

Table 7. Error variance decomposition for Norway emissions
Decomposition of Variance for Series SWEDCO2

| Step | Std Error  | FINCO2 | NORCO2 | SWEDCO2 |
|------|------------|--------|--------|---------|
| 1    | 4013.45826 | 14.879 | 0.414  | 84.707  |
| 2    | 5402.49414 | 14.879 | 0.414  | 84.707  |
| 3    | 6199.38159 | 11.835 | 0.429  | 87.736  |
| 4    | 6771.28803 | 10.090 | 0.437  | 89.472  |
| 5    | 7246.87623 | 10.156 | 0.437  | 89.407  |
| 6    | 7677.85332 | 11.750 | 0.429  | 87.821  |
| 7    | 8083.39659 | 14.369 | 0.417  | 85.214  |
| 8    | 8468.41917 | 17.530 | 0.401  | 82.069  |
| 9    | 8832.16596 | 20.862 | 0.385  | 78.753  |
| 10   | 9172.28683 | 24.122 | 0.369  | 75.509  |

Table 8. Error variance decomposition for Sweden emissions

In the first column of these tables are printed the estimated standard errors of the predictions, here 10 steps ahead. Each column shows the percentage of error due to each of the variables; as a consequence the total of each row is 100. Once again, these tables are in agreement with the three estimated models.

Forseeing the future

Once we get a validated model, we could attempt to foresee the future. From our simplified model, and using RATS package, we forecast the future from 2015 to 2020. The results are in table 8.

| ENTRY | FORECASTS(1) | FORECASTS(2) | FORECASTS(3) | STDERRS(1) | STDERRS(2) | STDERRS(3) |
|-------|--------------|--------------|--------------|-------------|-------------|-------------|
| 2015:01 | 48081.8313   | 43906.7905   | 45265.4167   | 4528.6095   | 4213.1769   | 4013.4582   |
| 2016:01 | 48750.7476   | 41469.7532   | 46913.1434   | 5961.9579   | 5049.9213   | 5402.4941   |
| 2017:01 | 49323.5202   | 40065.1047   | 48259.2924   | 6824.2045   | 5545.4613   | 6199.3815   |
| 2018:01 | 49813.9680   | 39313.0813   | 49353.6138   | 7392.7763   | 5995.6768   | 6771.2880   |
| 2019:01 | 50233.9235   | 38966.9882   | 50238.0735   | 7783.3060   | 6419.8433   | 7246.8762   |
| 2020:01 | 50593.5185   | 38867.4508   | 50948.0349   | 8057.6238   | 6797.2853   | 7677.8533   |

Table 8. Forecasts of emissions for 2015 to 2020, with standard errors

Results represented in figure 2

Figure 2. CO2 emissions 1960-2014 and forecasts 2015-2020, with confidence bands
The picture shows that the Norwegian series is falling down, while the other two series show a light rising path.

**Conclusions**

Our VAR(2) model has established a classification among our series of CO2 emissions, with the Finnish case been independent of the other two as well as affecting the CO2 emissions in Norway and Sweden. Apart from the data series alone, the strong economy of Norway shows a decreasing evolution in the immediate near future.

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