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Article

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

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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: Paris 2015 Agreement, 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.

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1. 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 goverments in Europe and the rest of the World due to its influence in the climate change. The Conference of Paris 2015: United Nations Climate Change Conference, has established five clear goals to slow the deterioration of the World Climate. It is worth to collect them here:

1.- Long term goal: governments agreed to keep the increase in global average temperature to well below 2ºC above pre-industrial levels and pursue efforts to limit it to 1.5ºC

2.- Governments agreed to establish comprehensive national climate action plans to reduce their emissions

3.- Goverments agreed to report every 5 years their contributions to set more ambitious targets

4.- Goverments accepted to communicate to each other and the public how well they are implementing their targets in order to ensure transparency and oversight

5.- The EU and other developed countries will continue to provide financial assistance to developing countries both to reduce emissions and build resilience to climate change impacts.

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

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location in the North of Europe, the three countries are facing similar problems in order to fulfill the Paris Agreement.

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

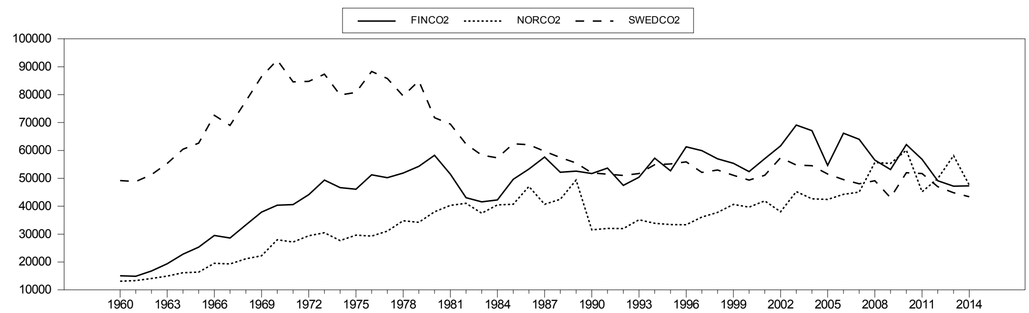

Figure 1. CO2 emissions in Finland, Norway and Sweden: 1960-2014

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

2. Materials and Methods

The data

The anual data are taken from the World Bank data base. The observations go from 1960 to 2014, and are measured in kilotonnes 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	13102.1910000	60105.7970000
SWEDCO2	55	61351.4435636	13891.4215466	43065.2480000	92379.0640000

Table 1. Basic statistics of the sample

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The figures for the CO2 emissions for the years 2009 to 2014, the last year reported in the World Bank data base, (as for September 2017) , 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* (Tsay, 2014, p. 27), and the author enumerates the computing advantages, as well as the objectives of the multivariate analysis: to study dynamic relationships between varibles, as well as to improve the accuracy of predictions, (cfr. Tsay, 2014, p. 1).

In order to introduce the VAR models, let us present its formulation. In our case, we have the vector of series $z_t = \begin{bmatrix} finCO2 \\ norCO2 \\ swedCO2 \end{bmatrix}$ for simplicity, let us use: $z_t = \begin{bmatrix} z_{1t} \\ z_{2t} \\ z_{3t} \end{bmatrix}$.

(The reason for this ordering is alphabetical.)

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

$$z_t = \phi_0 + \phi_1 z_{t-1} + \phi_2 z_{t-2} + a_t$$

With a_t as a sequence of independent and identically distributed (iid) random vectors, with mean zero and covariance matrix Σ_a, positive-definite.

In a more explicit form, we have,

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$$\begin{bmatrix} z_{1t} \\ z_{2t} \\ z_{3t} \end{bmatrix} = \begin{bmatrix} \phi_{10} \\ \phi_{20} \\ \phi_{30} \end{bmatrix} + \begin{bmatrix} \phi_{1,11} & \phi_{1,12} & \phi_{1,13} \\ \phi_{1,21} & \phi_{1,22} & \phi_{1,23} \\ \phi_{1,31} & \phi_{1,32} & \phi_{1,33} \end{bmatrix} \begin{bmatrix} z_{1,t-1} \\ z_{2,t-1} \\ z_{3,t-1} \end{bmatrix} + \begin{bmatrix} \phi_{2,11} & \phi_{2,12} & \phi_{2,13} \\ \phi_{2,21} & \phi_{2,22} & \phi_{2,23} \\ \phi_{2,31} & \phi_{2,32} & \phi_{2,33} \end{bmatrix} \begin{bmatrix} z_{1,t-2} \\ z_{2,t-2} \\ z_{3,t-2} \end{bmatrix} + \begin{bmatrix} a_{1t} \\ a_{2t} \\ a_{3t} \end{bmatrix}$$

The coefficients of matrices ϕ_1 and ϕ_2 allow us to related our model with the *Granger causality* point of view (cfr. Tsay, 2014, pp. 29, 37).

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
        [,1]    [,2]    [,3]
[1,]  0.7822  0.0407 0.07467
[2,] -0.1437  0.4993 0.00432
[3,]  0.0974 -0.0450 0.68347
standard error
      [,1]  [,2]  [,3]
[1,] 0.160 0.153 0.174
[2,] 0.143 0.137 0.156
[3,] 0.138 0.133 0.151
AR( 2 )-matrix
        [,1]    [,2]    [,3]
[1,]  0.0665 -0.0163 -0.0623
[2,]  0.3202  0.2136 -0.0142
[3,] -0.2427 -0.0318  0.2031
standard error
      [,1]  [,2]  [,3]
[1,] 0.166 0.164 0.166
[2,] 0.149 0.147 0.149
[3,] 0.144 0.142 0.144

Residuals cov-mtx:
         [,1]     [,2]     [,3]
[1,] 20351832  1927911  7295705
[2,]  1927911 16243125  1865395
[3,]  7295705  1865395 15255420
```

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```
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 = VARchi(zt,p=2,thres=1.96)
Number of targeted parameters:  16
Chi-square test and p-value:  27.01784 0.04128532
> m4 = refVAR(m2,thres=1.96)
Constant term:
Estimates:  7579.741 0 14517.27
Std.Error:  2528.822 0 3907.614
AR coefficient matrix
AR( 1 )-matrix
      [,1]  [,2]  [,3]
[1,] 0.856 0.000 0.000
[2,] 0.000 0.661 0.000
[3,] 0.000 0.000 0.901
standard error
       [,1]   [,2]   [,3]
[1,] 0.0505 0.0000 0.0000
[2,] 0.0000 0.0856 0.0000
[3,] 0.0000 0.0000 0.0433
AR( 2 )-matrix
       [,1] [,2] [,3]
[1,]  0.000    0    0
[2,]  0.263    0    0
[3,] -0.177    0    0
standard error
       [,1] [,2] [,3]
[1,] 0.0000    0    0
[2,] 0.0643    0    0
[3,] 0.0444    0    0

Residuals cov-mtx:
         [,1]     [,2]     [,3]
[1,] 20508305  1929612  7010868
[2,]  1929612 17750860  1742123
```

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```
[3,]   7010868   1742123 16107847

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

That is:

$$\begin{bmatrix} z_{1t} \\ z_{2t} \\ z_{3t} \end{bmatrix} = \begin{bmatrix} 7579.7 \\ 0.000 \\ 14517.3 \end{bmatrix} + \begin{bmatrix} 0.856 & 0.000 & 0.000 \\ 0.000 & 0.661 & 0.000 \\ 0.000 & 0.000 & 0.901 \end{bmatrix} \begin{bmatrix} z_{1,t-1} \\ z_{2,t-1} \\ z_{3,t-1} \end{bmatrix} + \begin{bmatrix} 0.0 & 0.0 & 0.0 \\ 0.263 & 0.0 & 0.0 \\ -0.18 & 0.0 & 0.0 \end{bmatrix} \begin{bmatrix} z_{1,t-2} \\ z_{2,t-2} \\ z_{3,t-2} \end{bmatrix} + \begin{bmatrix} \hat{a}_{1t} \\ \hat{a}_{2t} \\ \hat{a}_{3t} \end{bmatrix}$$

Therefore the models of CO2 emissions in each of the three countries can be written as:

For Finland,

$$z_{1t} = 7579.7 + 0.856 z_{1,t-1} + \hat{a}_{1t}$$

For Norway,

$$z_{2t} = 0.661 z_{2,t-1} + 0.263 z_{1,t-2} + \hat{a}_{2t}$$

For Sweden,

$$z_{3t} = 14517.3 + 0.901 z_{3,t-1} - 018 z_{1,t-2} + \hat{a}_{3t}$$

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, 1986, 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 posible 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.

$$z_t = \mu + a_t + \theta_1 a_{t-1} + \theta_2 a_{t-2} + \cdots$$

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

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

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

$$\begin{aligned} z_t - \mu &= \theta_i \\ &\vdots \\ z_{t-k-1} - \mu &= \theta_{t-k-1} \\ z_{t-k} - \mu &= \theta_{t-k} \end{aligned}$$

This series of θ_t are the coefficients of the impulse response in z_t of the unitary shock induced in a_t.

If Σ_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 imposible 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 Σ_a, given the fact that our matrix is positive definite. In this case, there is a matrix P, such that $\Sigma_a = PP'$ and $P'\Sigma_a P'^{-1} = I$. With this matrix P^{-1} it is possible to convert a_t on a vector of uncorrelated errors e_t, that is:

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

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 ortogonal innovations.

There is a problem involved with Cholesky decomposition of Σ_a, worth of mentionning. 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.

Responses to Shock in FINCO2

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

Responses to Shock in NORCO2

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
4	0.00000	1209.40524	188.9518
5	0.00000	799.16545	170.2634
6	0.00000	528.08224	153.4233

7	0.00000	348.95258	138.2488
8	0.00000	230.58512	124.5752
9	0.00000	152.36883	112.2539
10	0.00000	100.68412	101.1514

Table 4. Responses to shock in Norway emissions model

Responses to Shock in SWEDCO2

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

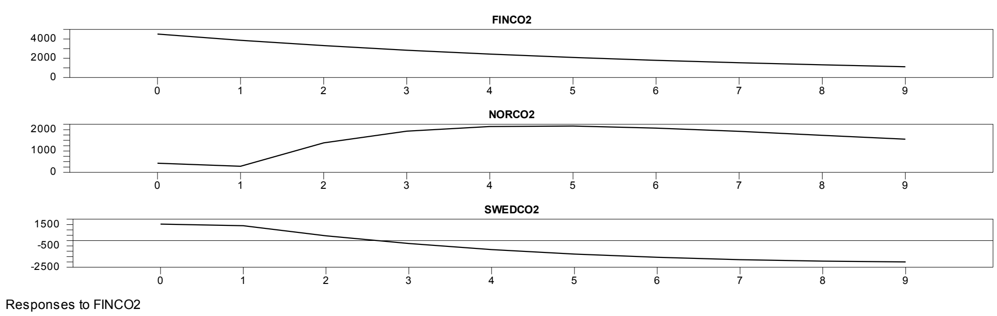

Figure 3. Representation of responses of shock in Finland emissions model

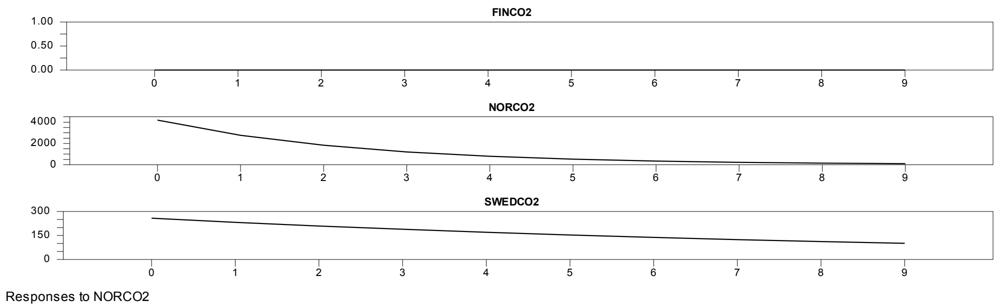

Figure 4. Representation of responses of shock in Norway emissions model

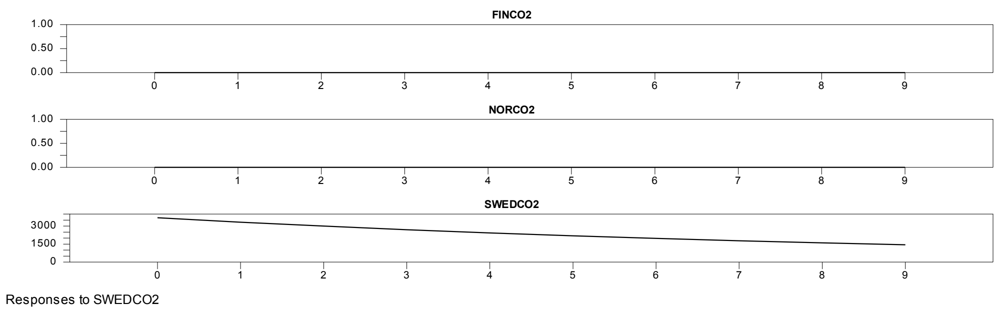

Figure 5. Representation of responses of shock in Sweden emissions model

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 schock induced. As a help to evaluate more exactly this effect, we have the forecast error variance decomposition. Now it is posible 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

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

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10	8568.31098	100.000	0.000	0.000

Table 6. Error Variance decomposition for Finland emissions

Decomposition of Variance for Series NORCO2

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 attemp to forseen the future. From our simplified model, and using RATS package, we forecast the future from 2015 to 2020.

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The results are in table 9.

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 9. Forecasts of emissions for 2015 to 2020, and their standard errors

These results are represented in figure 2

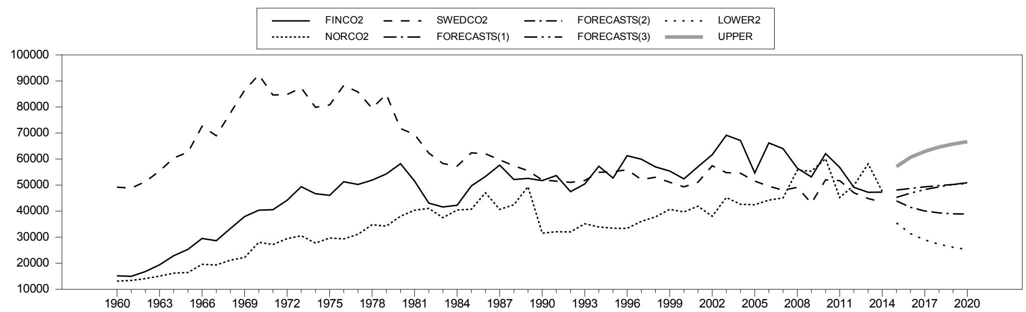

Figure 2. CO2 emissions 1960-2014 and their forecasts 2015-2010 with 95% confidence bands

The picture shows that the Norvegian series is falling down, while the other two series show a light rising path.

Results

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 inmediate near future.

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