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Wind electricity production in Germany and Spain: a dynamic relationship

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Abstract

In this paper, a dynamic relationship between the wind electricity production of Germany and Spain is presented. With the help of a VAR(1) model, and using the terminology of Granger Causality, it is shown that the wind electricity production of Germany Granger causes the wind electricity production of Spain. Other aspects of this dynamic relationship are presented as well.

JEL-classification: C01, C22, C32,C51.

Keywords

Wind electricity production. VAR models. Granger Causality. Impulse response functions. Forecast error variance decomposition. Software: R, RATS, MTS, VARS.

Introduction

A new energy economy is emerging: coal, oil and other fossil fuels are being replaced by solar and wind energy. This conclusion by Lester R. Brown and his collaborators at the Earth Policy Institute is of the greatest relevance in these days. (cf. Brown, 2015, p.3)

In the global transition from fossil fuels to wind and solar energy, wind has taken the early lead. This is another conclusion by the people at the Earth Policy Institute. (cf. Brown, 2015, p.84.)

Some characteristics of wind are worth mentioning.

Wind is abundant, carbon-free, and inexhaustible. It uses no water, no fuel and little land. It also scales up easily and can be brought online quickly. These advantages, together with a policy of public subsidies, explain why wind power is expanding so rapidly. (cf. Brown, 2015, pp. 84-89.)

Over the past decade wind power capacity grew more than 20 percent a year, due to its many attractive features, public policies supporting its expansion, and falling production costs.

The year 2013 ended with a bang for wind energy in Europe.

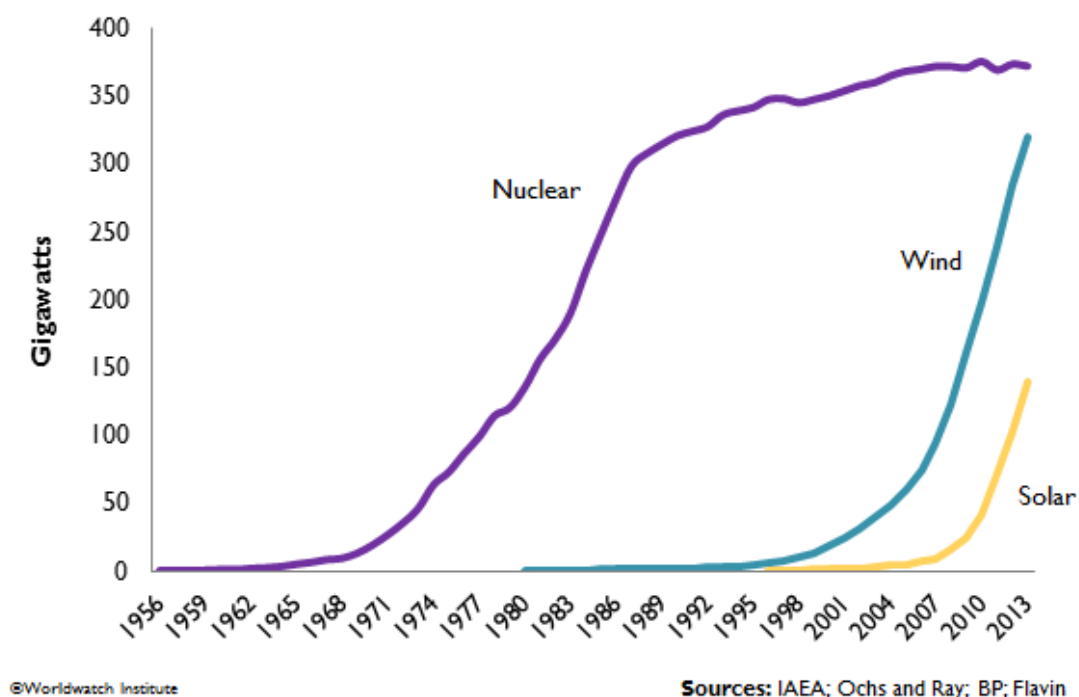
By the end of 2013, the wind farms installed in more than 85 countries had a combined generating capacity of 318000 megawatts. This would be enough to meet the residential electricity needs of the European Union's 506 million people (cf. J. Matthew Roney, April 2014)

The leaders in wind generating capacity are China and the United States. At the start of 2014, China had a 91000 megawatts wind generating capacity, followed by the United States with 61000 megawatts. Germany ranked third with 30000 megawatts, followed by Spain and India with around 20000 megawatts each. The United Kingdom, Italy, France and Canada clustered together in the range 8000-10000 megawatts range. (cf. J. Matthew Roney, 2014).

With these wind power achievements it is becoming easier to visualize the new energy economy.

Michael Renner, Worldwatch Institute, September 30, 2014, presented a graph showing the evolution of World nuclear, wind and solar generating capacity, from 1956 to 2013. It is reproduced here as figure 1.

Figure 1. | World Nuclear, Wind, and Solar Generating Capacity, 1956-2013



This picture is self explanatory, showing how wind generating capacity is approaching nuclear capacity.

By the way, the European Wind Energy Association, EWEA, in its press release of 15/06/2015 wrote that "multinational companies are turning to clean, reliable and cost-

effective wind energy” and this is an occasion to celebrate the Global Wind Day that occurs annually on 15 June.

Spain, for example, was, in 2013, the first country where wind energy was the first source of electricity for an entire year. (Press release of the AEE, 15/01/2014)

According to the 2013 advance report of the system operator Red Eléctrica de España, REE, the power demand coverage using wind was 20.9%, compared with 20.8% coming from nuclear sources.

Germany and Spain, are the two european countries with the highest wind power capacity: Germany produces 34250 megawatts and Spain 22959 megawatts. (cf. J. Matthew Roney, 2014)

This, however, is not the place to comment about the many capabilities of wind energy. The interested reader is directed to the book of Lester Brown and collaborators in the Earth Policy Institute (Brown, 2015).

The starting point for this paper is the data on Wind electricity generation, as recorded by eia.gov/beta/international/rankings, and reported by the Earth Policy Institute in 2013. I take the data for Germany and Spain with the intent of establishing a dynamic relationship between the wind electricity produced in both countries, via a VAR model of order one.

Data

This collection of data was compiled by the author from the eia.gov/beta/international/ and from the Earth Policy Institute: “Wind-generated electricity in top five Countries in the World, 2000-2013”, is a collection of twenty two years of generated wind electricity in Germany and Spain, in terawatts-hours, from 1992 to 2013.

The figures for the two series are in the following table: table 1

ENTRY	GERMANY	SPAIN
1992:01	0.3	0.1
1993:01	0.7	0.1
1994:01	1.4	0.2
1995:01	1.7	0.3
1996:01	2.1	0.4
1997:01	3.0	0.7
1998:01	4.6	1.4
1999:01	5.5	2.7
2000:01	9.4	4.7
2001:01	10.0	6.8
2002:01	16.0	9.3
2003:01	19.0	12.0
2004:01	26.0	16.0
2005:01	27.0	21.0
2006:01	31.0	23.0

2007:01	40.0	28.0
2008:01	41.0	33.0
2009:01	39.0	38.0
2010:01	38.0	44.0
2011:01	47.0	42.0
2012:01	51.0	49.0
2013:01	53.0	56.0

Table 1

Using RATS, each temporal evolution is represented in figure 2.

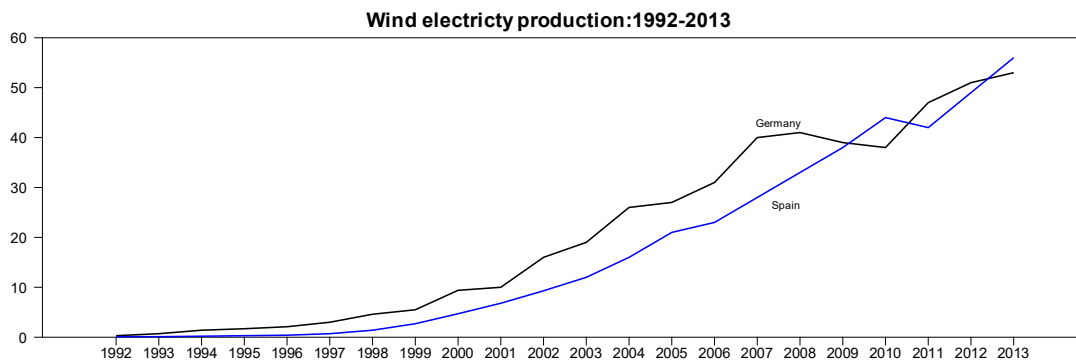


Fig. 2 Temporal wind electricity production for Germany and Spain: 1992-2013 At a first look, the two series seem to be non stationary, but with VAR models their transformation is not recommended (Cf. RATS, User's Guide, p. 205, versión 8.)

The basic statistics, mean and standard deviation of both series are as follows:

Series	Obs	Mean	Std Error	Minimum	Maximum
GERMANY	22	21.21363636	18.52438021	0.30000000	53.00000000
SPAIN	22	17.66818182	18.54370350	0.10000000	56.00000000

VAR(p) models

According to Tsay (2014, p. 27) the most commonly used econometric model for multiple time series is the multiple vector autoregressive or VAR model. There are good reasons for this assertion.

The multivariate time series z_t follows a VAR model of order p if it can be written as:

$$z_t = \phi_0 + \sum_{i=1}^p \phi_i z_{t-i} + a_t$$

with z_t a vector of time series of dimension $k \times 1$

ϕ_0 a vector of constants of dimension: $k \times 1$

ϕ_i a matrix of dimension $k \times k$, for $i > 0$ and $\phi_p \neq 0$, and

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

To summarize the properties of VAR(p) models, it is interesting to start with the bilinear VAR(1):

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

written explicitly as:

$$\begin{pmatrix} z_{1t} \\ z_{2t} \end{pmatrix} = \begin{pmatrix} \phi_{10} \\ \phi_{20} \end{pmatrix} + \begin{pmatrix} \phi_{1,11} & \phi_{1,12} \\ \phi_{1,21} & \phi_{1,22} \end{pmatrix} \begin{pmatrix} z_{1,t-1} \\ z_{2,t-1} \end{pmatrix} + \begin{pmatrix} a_{1t} \\ a_{2t} \end{pmatrix}$$

or:

$$\begin{aligned} z_{1t} &= \phi_{10} + \phi_{1,11} z_{1,t-1} + \phi_{1,12} z_{2,t-1} + a_{1t} \\ z_{2t} &= \phi_{20} + \phi_{1,21} z_{1,t-1} + \phi_{1,22} z_{2,t-1} + a_{2t} \end{aligned}$$

That is, $\phi_{1,12}$ shows the linear dependence of z_{1t} on $z_{2,t-1}$ in the presence of $z_{1,t-1}$. And $\phi_{1,21}$ measures the linear relationship between z_{2t} and $z_{1,t-1}$ in the presence of $z_{2,t-1}$ and similarly with the other coefficients of matrix ϕ_1 .

This matrix representation of the model, gives us the insight of the so called Granger Causality.

If the off-diagonal elements of matrix ϕ_1 are zero, that is $\phi_{1,12} = \phi_{1,21} = 0$ the consequence is that z_{1t} and z_{2t} are not dynamical correlated, in which case each series follows a univariate AR(1) model, that can be handled accordingly. The two series are said to be uncoupled. (Tsay, 2014, p. 28)

On the other side, if $\phi_{1,12} = 0$ but $\phi_{1,21} \neq 0$ then we have:

$$z_{1t} = \phi_{10} + \phi_{1,11} z_{1,t-1} + a_{1t}$$

and

$$z_{2t} = \phi_{20} + \phi_{1,21} z_{1,t-1} + \phi_{1,22} z_{2,t-1} + a_{2t}$$

That is, z_{1t} does not depend on the past values of z_{2t} but z_{2t} depends on the past values of z_{1t} . This is an example of a transfer function relationship, in control engineering. In econometrics, this is an example of Granger Causality between two series, with z_{1t} Granger causing z_{2t} but z_{1t} not being Granger caused by z_{2t} .

As Tsay (2014, p.29) remarks for this bivariate VAR(1) model, if the variance-covariance matrix Σ_a is not diagonal, then z_{1t} and z_{2t} are instantaneously or contemporaneously correlated, with instantaneous Granger causality, going in both directions.

In our case, the bivariate vector z_t is

$$z_t = \begin{pmatrix} z_{1t} \\ z_{2t} \end{pmatrix}$$

with Germany as z_{1t} and Spain as z_{2t} .

Next, the number of lags of the model has to be determined. With the help of the RATS package, and using the Akaike information criterion (AIC), corrected for degrees of freedom, the order of our VAR is

```
@varlagselect(lags=7,crit=aic)
# Germany Spain
```

```
VAR Lag Selection
Lags AICC
  0 14.3814101
  1  9.7230481*
  2 10.4747166
  3 11.2770593
  4 12.0198686
  5 15.7624904
  6 36.0514213
  7      NA
```

That is, $p = 1$. With this value of p , we can estimate the VAR(1) model. Using the MTS package, we get:

```
m1 = VAR(zt,p=1)
Constant term:
Estimates:  2.148936 -0.2586105
Std.Error:  1.145812 0.5067728
AR coefficient matrix
AR( 1 )-matrix
      [,1] [,2]
[1,] 0.925 0.116
[2,] 0.387 0.704
standard error
      [,1] [,2]
[1,] 0.1759 0.1830
[2,] 0.0778 0.0809

Residuals cov-mtx:
```

```

          [,1]      [,2]
[1,]  8.4070018 -0.9003846
[2,] -0.9003846  1.6445279

```

```

det(SSE) = 13.01486
AIC = 2.929728
BIC = 3.128099
HQ = 2.976458

```

This estimated model has non-significant coefficients at the usual $\alpha = 0.05$ significance level. Suppressing these coefficients, we get the simplified model: m2

```

> m2 = refVAR(m1, thres=1.96)
Constant term:
Estimates:  0 0
Std.Error:  0 0
AR coefficient matrix
AR( 1 )-matrix
      [,1] [,2]
[1,] 1.087 0.000
[2,] 0.364 0.721
standard error
      [,1] [,2]
[1,] 0.0272 0.0000
[2,] 0.0632 0.0722

```

```

Residuals cov-mtx:
      [,1]      [,2]
[1,] 10.062045 -1.098087
[2,] -1.098087  1.668320

```

```

det(SSE) = 15.58092
AIC = 3.018774
BIC = 3.167553
HQ = 3.053822

```

Finally, this model with significant coefficients, and validating residuals, can be written:

$$\begin{pmatrix} z_{1t} \\ z_{2t} \end{pmatrix} = \begin{pmatrix} 0.00 \\ 0.00 \end{pmatrix} + \begin{pmatrix} 1.087 & 0.000 \\ 0.364 & 0.721 \end{pmatrix} \begin{pmatrix} z_{1,t-1} \\ z_{2,t-1} \end{pmatrix} + \begin{pmatrix} \hat{a}_{1t} \\ \hat{a}_{2t} \end{pmatrix}$$

With a variance-covariance matrix of residuals

$$\Sigma_{\hat{a}} = \begin{pmatrix} 10.062 & -1.098 \\ -1.098 & 1.668 \end{pmatrix}$$

Written separately, the two estimated models, are as follows:

$$\hat{z}_{1t} = 0 + 1.087 z_{1,t-1}$$

and

$$\hat{z}_{2t} = 0 + 0.364z_{1,t-1} + 0.721z_{2,t-1}$$

In words, the production of wind electricity in Germany, in the presence of the wind electricity produced by Spain depends on its lagged first period, while the wind electricity produced by Spain, in the presence of the wind electricity produced by Germany, depends on its lagged first period, and on the lagged first period of Germany. If we employ the terminology of Granger Causality, we can say that the wind electricity produced by Germany Granger causes the wind electricity produced by Spain.

Since the matrix variance-covariance matrix $\hat{\Sigma}_a$ is not diagonal, then both series are instantaneously or contemporaneously correlated.

In case we would like to be formal, using package VARS in R, we get:

```
causality(m2, cause="germany")
$Granger
```

```
Granger causality H0: germany do not Granger-cause spain
```

```
data: VAR object m2
F-Test = 24.682, df1 = 1, df2 = 36, p-value = 1.656e-05
```

```
$Instant
```

```
H0: No instantaneous causality between: germany and
spain
```

```
data: VAR object m2
Chi-squared = 1.4073, df = 1, p-value = 0.2355
```

```
> causality(m2, cause="spain")
$Granger
```

```
Granger causality H0: spain do not Granger-cause germany
```

```
data: VAR object m2
F-Test = 0.39955, df1 = 1, df2 = 36, p-value = 0.5313
```

```
$Instant
```

```
H0: No instantaneous causality between: spain and
germany
```

```
data: VAR object m2
Chi-squared = 1.4073, df = 1, p-value = 0.2355
```

Results that confirm our previous conclusions.

The impulse response

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

It is of interest to evaluate the effects of a stochastic change or shock in one variable, to its own evolution and to the evolution of the others variables. This type of analysis is known as the impulse response or multiplier analysis.

The impulse response measures the effect of a shock caused in one variable of the system on its own and on the rest of the variables. This effect it is better understood in the MA versión of the VAR model.

$$z_t = \mu + a_t + \theta_1 a_{t-1} + \theta_2 a_{t-2} + \theta_3 a_{t-3} + \dots$$

truncated at some lag, q , with $\theta_0 = 1$ and a_t a succession of iid random innovations, having mean zero and constant variance.

In compact form:

$$z_t = \mu + \sum_{i=0}^q \theta_i a_{t-i}; \theta_0 = 1$$

If we now induce a unitary impulse or a shock in a_t that is, if we set to zero all the a_t except one, a_{t-k} , which is set to 1, then by successive substitutions, we get:

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

This succession of values of θ_i is called the impulse response on z_t of the unitary shock 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 can be isolated from the other errors' terms. That is, it would be impossible to establish the impact of a unitary shock on the wind electricity produced by Germany on the wind electricity produced by Spain. To solve this problem we could use the Cholesky decomposition of matrix Σ_a , a solution possible due to the fact that this matrix is symmetric and positive-definite. In this case, there is a matrix P such that $\Sigma_a = PP'$ and $P'\Sigma P'^{-1} = I$. With this 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 $e_t = P^{-1} a_t$, the elements of B_i are the impulse response coefficients of z_t with orthogonal innovations.

It should be mentioned that the problem involved in the Cholesky decomposition of Σ_a , is that the order of variables in the vector z_t has consequences, but 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 .

In this case, using the software RATS, the impulse response of a unitary shock in the wind electricity produced by Germany is:

Responses to Shock in GERMANY		
Entry	GERMANY	SPAIN
1	3.17207272	-0.3461733
2	3.44820676	0.9061026
3	3.74837872	1.9093622
4	4.07468113	2.7418843
5	4.42938869	3.4608558
6	4.81497412	4.1083266
7	5.23412538	4.7155078
8	5.68976443	5.3058762

The impulse response of a unitary shock in the wind electricity produced by Spain is:

Responses to Shock in SPAIN		
Entry	GERMANY	SPAIN
1	0.00000000	1.2443810
2	0.00000000	0.8969694
3	0.00000000	0.6465497
4	0.00000000	0.4660432
5	0.00000000	0.3359313
6	0.00000000	0.2421445
7	0.00000000	0.1745416
8	0.00000000	0.1258123

The graphical representation of these responses is depicted in fig. 3

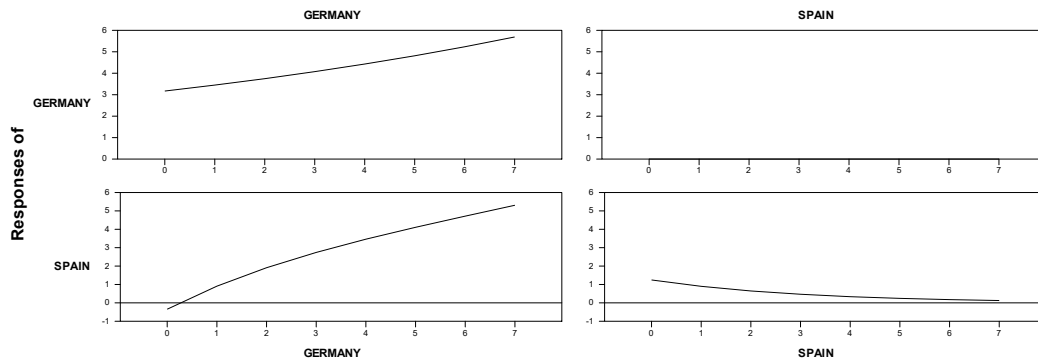


Fig. 3. Impulse responses

The forecast error variance decomposition

Another point of view for the dynamic relationship established by a VAR model is given by the forecast error variance decomposition, (FEVD), which permits the assignment of the fraction of the variance of the error due to each of the variables in the system. In other words, this decomposition allows us to tribute the error variance at the sources.

With RATS, this is the decomposition in our case:

Decomposition of Variance for Series GERMANY

Step	Std Error	GERMANY	SPAIN
1	3.1720727	100.000	0.000
2	4.6853148	100.000	0.000
3	6.0002098	100.000	0.000
4	7.2529680	100.000	0.000
5	8.4985310	100.000	0.000
6	9.7677533	100.000	0.000
7	11.0817450	100.000	0.000
8	12.4570660	100.000	0.000

Decomposition of Variance for Series SPAIN

Step	Std Error	GERMANY	SPAIN
1	1.2916346	7.183	92.817
2	1.8149094	28.564	71.436
3	2.7124871	62.337	37.663
4	3.8849340	80.201	19.799
5	5.2137400	88.592	11.408
6	6.6422937	92.838	7.162
7	8.1477939	95.194	4.806
8	9.7239239	96.609	3.391

In the first column of these tables are the estimated standard errors of the predictions, here to a horizon of 8 periods (years). In the rest of the columns, the percentage of the variance due to each of the variables. The sum of each row adds to the total. In the first table the 100% of the error variance is due to Germany. In the second table, the percentage of the error variance is distributed between Germany and Spain.

We can request the forecast from 2008 to 2017 using RATS. These are the figures:

Entry	GERMANY	SPAIN
2008:01	43.48206448	34.75539137
2009:01	47.26724830	40.89334784
2010:01	51.38193846	46.69667807
2011:01	55.85481904	52.37884813
2012:01	60.71707108	58.10417773
2013:01	66.00259000	64.00247079
2014:01	71.74822187	70.17964059
2015:01	77.99402025	76.72545460
2016:01	84.78352544	83.71921071
2017:01	92.16406802	91.23393042

Once again we can see how closely the series and the forecasts move.

Conclusion

The main conclusion of this paper is the relevance of Germany and Spain in the generation of wind electricity, in Europe, confirming the German position of leadership according to the Granger Causality Principle. Another relevant conclusion is that both countries are working firmly in the direction established by United Nations for climate preservation.

At this moment, the critical point is the future of public subsidies. The economic crisis of these days suggests to hold back the policy of public aids. However, the worries about the climate change, works in favor of maintaining policy to help fund renewable sources of energy, and wind energy is one.

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