

Structural Break, Stock Prices of Clean Energy Firms and Carbon Market

Yubao Wang and Junyu Cai¹

1 School of Economics and Finance, Xi'an Jiaotong University, Xi'an, China
E-mail: jacky.mucklow@iop.org

Abstract. This paper uses EU ETS carbon future price and Germany/UK clean energy firms stock indices to study the relationship between carbon market and clean energy market. By structural break test, it is found that the 'non-stationary' variables judged by classical unit root test do own unit roots and need taking first difference. After analysis of VAR and Granger causality test, no causal relationships are found between the two markets. However, when Hsiao's version of causality test is employed, carbon market is found to have power in explaining the movement of stock prices of clean energy firms, and stock prices of clean energy firms also affect the carbon market.

1. Introduction

There have existed studies on the relationship between clean energy and typically traditional economic variables such as oil price, high technology stock and interest rate [1]-[8]. However, once taking the relationship between stock prices of clean energy firms and carbon market into account, few studies are applicable. For this paper, only two papers may be directly referred to in such a field: those of Kumar et al. (2012) [9] and Zhu and Kong (2016) [10]. However, their conclusions differ: Kumar failed to find a significant relationship between the two markets, while Zhu and Kong found that carbon price would affect the stock prices of clean energy firms.

2. Data

For studying relationship between stock prices of clean energy firms and carbon market, clean energy firms' stock prices, high technology firms' stock prices, oil price, carbon price and interest rates would be discussed.

2.1 Time frame and carbon price

Time ranged from 01/08/2014 to 12/14/2016, totally 154 weekly observations available. The Wednesday data for the variables discussed below were adopted and closing prices from the most recent trading session would make up for the missing data at that day. And for the continuity of data and reflection of the potential equilibrium of the markets, closing prices of carbon future were utilized. The EUA data were from WIND.

2.2 Index constructing

Index for certain purpose of research may not be available at hand but could be constructed effectively in some way (B.T. Katangodage and Wijeratne, 2016 [11]). And to avoid coming across survivor-ship bias discussed by Rohleder et al. (2011) [12], value-weighted approach proved to be more efficient than equally-weighted approach practically is adopted (Ibbotson et al., 2011[13]).



Four companies of DAX index were selected for Germany: companies of E.ON.SE, Infineon Technologies AG, RWE AG and Siemens Aktiengesellschaft. And UK is also checked. Seven companies from FTSE 350 were chosen: companies of Centrica plc, Drax Group plc, National Grid plc, Severn Trent, SSE plc, United Utilities Group plc and Vedanta Resources plc.

Four companies in the DAX were chosen for high technology firm stock index constructing: companies of Bayer AG, Deutsche Telekom AG, Merck KgaA and SAP SE., while UK all-share technology index was available.

2.3 Interest rates and oil price

EURIBOR three-month funds and Euro deposit rates (GBP-3 Month-rate value) were adopted to respectively stand for interest rates of Germany and UK. Oil price was obtained by the average of the closing price of West Texas Intermediate (WTI) and that of the BRENT crude oil futures contract.

3. Methodology and empirical results

All variables took logarithms with Germany and UK interest rates as exceptions. Interest rate for Germany turned into negative after April 15, 2015, which is inappropriate for logarithm. To keep consistency with Germany, UK interest rate would not be taken logarithm, either.

3.1 Statistics summary for investment choice

Table 1 shows the descriptive statistics of weekly continuously compounded returns for investments on different assets. Annual returns for each asset is obtained by multiplying 52. For investments in Germany and UK clean energy firms, the returns are 13.52% and 6.76%, respectively twice and four times their corresponding market index. Further, traditional Sharpe ratio shows that oil would not be appealing for investors in these years with negative Sharpe ratio, a difference from Kumar et al.(2012) [9] for whom oil ranked the first.

Table 1 Descriptive statistics of weekly returns.

Variable	Obs	Mean	S. Dev	Min	Max	Skewness	Kurtosis	Sharpe
Carbon price	153	5.7e-05	0.0554	-0.2289	0.2093	-0.5589	6.4588	0.005
Oil price	153	-0.0042	0.0506	-0.1440	0.1836	0.5102	4.5843	-0.079
Dax index	153	0.0011	0.0287	-0.0662	0.0711	-0.1693	2.7125	0.046
Germany high tech	153	-0.0010	0.2627	-0.8565	0.6697	-0.3108	3.9403	-0.003
Germany clean energy	153	0.0026	0.1152	-0.3280	0.3374	0.1702	4.1886	0.024
FTSE 350 index	153	0.0003	0.0209	-0.0647	0.0577	-0.0287	3.6310	-0.278
UK high tech	153	0.0027	0.0301	-0.0674	0.2159	2.1874	18.141	-0.114
UK clean energy	153	0.0013	0.0840	-0.3853	0.3427	-0.0778	6.6610	-0.057
Germany interest rate	154	-0.022%	0.0020	-0.316%	0.339%	0.1422	1.9176	/
UK interest rate	154	0.612%	0.0007	0.420%	0.790%	-0.4600	2.7854	/

3.2 Traditional unit root test

The results of ADF tests are displayed in Table 2, showing that only half of variables are stationary, i.e., variables of Germany high technology firms stock, Germany clean energy firms stock, FTSE 350 index, UK clean energy firms stock and UK interest rate.

Simply considering the traditional ADF test would urge the remaining five variables, i.e. carbon price, oil price, DAX index, UK high technology firms stock and Germany interest rate, to take first difference. However, Perron (1989) [14] emphasized that de-trended data in essence may be labeled with “non-stationary” when structural breaks exist. Further, Bai and Perron (2003) [15] proposed a model that finds the global structural breaking date with appropriate variables $\{Z_t\}$. Therefore, it is necessary to check whether structural break date exists in the five “non-stationary” time series before simply taking the first difference.

Table 2 Traditional ADF test.

	Level			First difference		
	Intercept and trend	Intercept	None	Intercept and trend	Intercept	None
Carbon price	-2.3811	-2.1324	-0.2603	-10.042***	-9.97***	-10.0***
Oil price	-0.8217	-1.3762	-1.1494	-11.617***	-11.5***	-11.52***
Dax index	-2.5044	-2.3121	0.4564	-12.800***	-12.8***	-12.9***
Germany high tech	-9.7411***	-7.784***	0.1996	-10.511***	-10.5***	-10.6***
Germany clean energy	-3.9345**	-1.6653	0.3471	-20.613***	-20.6***	-20.7***
FTSE 350 index	-2.8304	-2.8781*	0.1268	-14.600***	-14.6***	-14.7***
UK high tech	-2.3579	-0.4517	1.0794	-11.416***	-11.4***	-11.4***
UK clean energy	-5.6740***	-3.3866**	0.1116	-14.515***	-14.6***	-14.6***
Germany interest rate	-2.3378	-0.7388	-0.4201	-7.5904***	-7.6***	-6.69***
UK interest rate	-2.6516	-2.742*	-0.1494	-16.570***	-16.6***	-16.6***

***1 percent of significance

**5 percent of significance

* 10 percent of significance

3.3 Structural breaks

$\{Z_t\}$ is important for Bai and Perron (2003) [15] to find the global structural break dates. In their paper, $\{Z_t\}$ refers to the lag value of time series themselves, the time trend or just a constant term; and data generating processes for time series normally could capture these information. However, data generating process is hard to get. In order to get the data generating process, four models, used by Wang (2001) [16] and Wang and Chen (2007) [17], in Table 3 are assumed.

Table 3 Four models of data generating process.

	Model I	Model II	Model III	Model IV
	$y_t = y_{t-1} + u_t$	$y_t = c + y_{t-1} + u_t$	$y_t = c + \beta t + u_t$	$y_t = c + \beta t + y_{t-1} + u_t$
carbon	0.9194 (-2.922)	0.9206 (-2.910)	0.0284 (-0.396)	0.9219 (-2.901)
oil	0.9818 (-3.107)	0.9819 ^a (-3.085)	0.6941 ^b (-0.253)	0.9817 ^c (-3.052)
dax	0.8535 (-4.234)	0.8576 (-4.236)	0.1151 (-2.410)	0.8575 ^d (-4.210)
UK high tech	0.9691 (-4.143)	0.9689 (-4.111)	0.7205 ^b (-1.920)	0.9699 (-4.119)
Germany interest rate	0.9978 ^b (-15.658)	0.9982 (-15.811)	0.9723 ^b (-13.076)	0.9982 ^c (-15.792)

a: parameter of constant C is not statistically significant;

b: R^2 larger than DW statistics;

c: parameter time and constant C are not statistically significant;

d: parameter of time is not statistically significant.

Adjusted R square and Schwarz criteria are showed in the upper row and in brackets, respectively. And optimal model selection should satisfy the following conditions simultaneously: (1) highest adjusted R square; (2) lowest Schwarz criterion; (3) R squared value less than DW statistics in order to avoid problem of spurious regression (Granger and Newbold, 1974 [18]); and (4) significant coefficients. Overall, Model I suits carbon price, oil price and UK high technology index, and Model II suits Dax index and Germany interest rate. Therefore, for the former three variables, $\{Z_t\}$ employs $\{y(-1)\}$, while for the latter two, $\{1, y(-1)\}$ is chosen, where “ $y(-1)$ ” and “1” stand for lag term and constant term, respectively.

BP test is provided by E-views 8.0 for detecting structural breaks. From Table 4, no structural break dates exist in the five “non-stationary” time series. Such a finding justifies the conclusion in Table 2 that carbon price, oil price, Dax index, UK high technology firms stock and Germany interest rate do own unit roots and need taking first difference.

Table 4 BP test for seeking global structural break dates.

Variables	Sup F(0 1)	Z_t
Carbon price	2.377	{y(-1)}
Oil price	7.269	{ y(-1)}
Dax index	3.882	{1, y(-1)}
UK high tech	2.674	{ y(-1)}
Germany interest rate	0.0786	{1, y(-1)}

3.4 VAR analysis and Granger causality test

To select an appropriate lag length for VAR model, this paper resorts to Kumar et al (2012)^[9]: if criteria of FPE, AIC, SC and HQ showed different lags, the Likelihood Ratio test would be adopted. In Table 5, the chosen lags by FPE, AIC, SC and HQ are the same. Therefore, the VAR is estimated with one lag for both Germany and UK.

Tabel 5 Lag for VAR.

lag	Germany					UK				
	LR	FPE	AIC	SC	HQ	LR	FPE	AIC	SC	HQ
0	NA	8.6e-20	-26.9	-26.8	-26.8	NA	3.6e-20	-27.7	-27.6	-27.7
1	264.6	2e-20*	-28.3*	-27.4*	-27.9*	523	1.4e-21*	-31.0*	-30.2*	-30.7*
2	56.61	2.2e-20	-28.3	-26.6	-27.6	49	1.5e-21	-30.9	-29.3	-30.3

Table 6 VAR model fit and Lagrange-multiplier test.

VAR model fit				
Equation	parameters	R ²	F-statistics	
Germany				
Germany clean energy index	7	0.719427	61.96670	
Germany high tech index	7	0.235464	7.442937	
Oil prices	7	0.039411	0.991517	
Carbon prices	7	0.055775	1.427509	
Germany interest rate	7	0.209035	6.386747	
DAX index	7	0.019190	0.472829	
UK				
UK clean energy index	7	0.289163	9.830831	
UK high tech index	7	0.050887	1.295690	
Oil prices	7	0.032905	0.822270	
Carbon prices	7	0.076428	1.999851	
UK interest rate	7	0.753389	73.82857	
FTSE 350 index	7	0.788946	90.33797	
Lagrange-multiplier test				
lag	Germany		UK	
	LM statistics	Probability	LM statistics	Probability
1	50.05374	0.0599	50.83750	0.0516
2	38.59113	0.3533	35.22882	0.5021

H₀: no serial correlation at lag order.

In Table 6. As for the VAR model for Germany, only clean energy firms stock equation owns a high R squared value as well as high F statistics. For UK, interest rate equation and FTSE 350 index equation exhibit a high R squared values as well as F statistics followed by clean energy index equation with lower R squared value but higher F statistics. The Lagrange-multiplier test statistics in Table 6 reveal that VAR models are free from serial correlation at the significance of 1%. All of the eigenvalues are found to lie inside the unit circle; therefore, VAR model satisfies the stability condition and Granger causality test could proceed.

Even though this paper endeavors to capture the relationship between carbon price and corresponding European clean energy firms stock, stock prices of both Germany and UK clean energy firms do not “Granger” cause the carbon price. And carbon price does not “Granger” cause Germany or UK clean energy firms stock prices, either (see Table 7).

Table 7 Granger causality Wald tests.

Granger causality for UK					
Dependent variable: clean energy			Dependent variable: carbon price		
excluded	Chi-sq	prob.	excluded	Chi-sq	prob.
Carbon	0.000115	0.9915	Oil	0.008554	0.9263
Oil	1.339988	0.2470	FTSE 350 index	0.864378	0.3525
FTSE 350 index	0.759843	0.3834	clean energy	0.785536	0.3755
interest rate	0.615504	0.4327	interest rate	0.259615	0.6104
high tech index	4.730982	0.0296	high tech	2.783351	0.0952
All	5.674341	0.3392	All	5.759074	0.3304
Granger causality for Germany					
Dependent variable: clean energy			Dependent variable: carbon price		
excluded	Chi-sq	prob.	Excluded	Chi-sq	prob.
Carbon	0.026357	0.8710	DAX	0.234231	0.6284
DAX	3.728012	0.0535	Oil	0.018670	0.8913
Oil	1.103068	0.2936	clean energy	0.893183	0.3446
interest rate	0.280802	0.5962	interest rate	0.008955	0.9246
high tech	1.739218	0.1872	high tech	0.355254	0.5512
All	6.130239	0.2938	All	2.461510	0.7823

3.5 Hsiao's version of Granger causality test

It seems that there is no Granger causality between the two countries' clean energy firms stock and carbon price. However, VAR model is subject to chosen lag. To overcome such a problem, Hsiao's version of Granger causality test would be used. The formulas (1) and (2), (3) and (4) come from Hsiao's (1981) [19] and Altinay and Karagol (2004) [20], respectively.

$$y_t = \sum_{i=1}^M a_i y_{t-i} + \sum_{j=1}^N b_j x_{t-j} + u_t \quad (1)$$

$$x_t = \sum_{i=1}^M c_i x_{t-i} + \sum_{j=1}^N d_j y_{t-j} + v_t \quad (2)$$

$$FPE(m,0) = \left(\frac{T+m+1}{T-m-1} \right) \left(\frac{Q(m,0)}{T} \right) \quad (3)$$

$$FPE(m,n) = \left(\frac{T+m+n+1}{T-m-n-1} \right) \left(\frac{Q(m,n)}{T} \right) \quad (4)$$

where M and N donate the maximum lag orders, X_t and Y_t donate the two stationary time series, u_t and v_t stand for white noise.

Hsiao employs Akaike's final prediction error criterion to determine the lag order of auto-regressive models (1) and (2). Detailed conduct of running model (1) and (2), and FPE calculations of model (3) and (4) could be referred to Altinay and Karagol (2004). Only the judging rule is put here: when the

minimum FPE from equation (4) is smaller than that from equation (3), then X_t is said to cause Y_t in the equation (1). Same rule applies for equation (2).

Here, X_t donates stock prices of clean energy firms of each country and Y_t donates the carbon price. 52 weeks are there in a year; therefore, the maximum lag order for Germany and UK is set as 52. In Table 8, for Germany, the minimum FPE of the controlled variable (carbon price) is found at lag 50. After adding the manipulated variable (stock price of clean energy firms) into the model with the lag order of the controlled variable as 50, the minimum FPE (0.000091) is found at lag 51, smaller than the initial FPE (0.001917); therefore, Germany clean energy stock index does “Granger” cause carbon price. And likewise, it is found that carbon market also affects stock prices of clean energy firms. Same results hold for UK.

Table 8 Hsiao’s version of Granger causality test.

Germany				
Direction	Controlled variables	Minimum FPE	Manipulated variables	Minimum FPE
Equation (1): from X_t to Y_t	Carbon(50,0)	0.001917	Clean energy (50,51)	0.000091
Equation (2): from Y_t to X_t	Clean energy (50,0)	0.008006	Carbon(50,51)	0.000003
UK				
Direction	Controlled variables	Minimum FPE	Manipulated variables	Minimum FPE
Equation (1): from X_t to Y_t	Carbon(50,0)	0.001917	Clean energy (50,51)	0.000315
Equation (2): from Y_t to X_t	Clean energy (48,0)	0.003827	Carbon(48,52)	0.000093

4. Implication

Findings of this paper have important implications for China. As carbon market would be affected by the clean energy industry, the Chinese government should make sure the effective operating and reasonable pricing of clean energy industry, which allows the forthcoming carbon market to operate under an overall effective environment. Equally, carbon market should also be cultivated to be mature for the development of clean energy industry, due to the reason that clean energy firms are affected by the carbon price.

5. References

- [1] Henriques I and Sadorsky P 2008 *J. Energy. Economics* **30** 998-1010
- [2] Sadorsky P 2012 *J. Energy. Economics* **34** 248-55
- [3] Broadstock D C, Cao H and Zhang D 2012 *J. Energy. Economics* **34** 1888-95
- [4] Managi S and Okimoto T 2013 *J. Japan. And. The. World. Economy* **7** 1-9
- [5] Wen X, Guo Y and Wei Y 2014 *J. Energy. Economics* **41** 63-75
- [6] Reboredo J C 2015 *J. Energy. Economics* **48** 32-45
- [7] Reboredo J C and Wen X 2015 *J. Renewable. And. Sustainable. Energy. Reviews* **45** 624-36
- [8] Bondia R, Ghosh S and Kanjilal K 2016 *J. Energy* **101** 558-65
- [9] Kumar S, Managi S and Matsuda A 2012 *J. Energy. Economics* **34** 215-26
- [10] Zhu D, Kong Y 2016 *J. Ecological. Economy* **1** 52-7
- [11] Katangodage B T and Wijeratne A W 2016 *J. International. Journal. Of. Agricultural Resources, Governance and Ecology* **12** 27-52
- [12] Rohleder M, Scholz H and Wikens M 2011 *J. Review. Of. Finance* **15** 441-74
- [13] Ibbotson R G, Peng C and Zhu K X 2011 *J. Financial. Analysts. Journal* **67** 15-25
- [14] Perron P 1989 *J. Econometrica* **57** 1361-1401
- [15] Bai J and Perron P 2003 *J. Applied. Econometrics* **18** 1-22
- [16] Wang S 2001 *J. Statistics. And. Decision* **6** 4-5

- [17] Wang Y, Chen N 2007 *J. Statistics. And. Information. Forum* **22** 69-72
- [18] Granger C W J and Newbold P 1974 *J. Econometrics* **2** 111-20
- [19] Hsiao C 1981 *J. Monetary. Economics* **7** 85-106
- [20] Altinay G and Karagol E 2004 *J. Energy. Economics* **26** 985-94