Chapter 2
European Carbon Futures Prices Drivers During 2006–2012

Abstract This chapter discusses the main driving factors behind carbon prices in detail. It presents key data, then proceeds with the results of cointegration test, Granger causality test, and ridge regression estimation. The chapter provides as well a comparative analysis of the equilibrium carbon price and observed carbon price, before drawing conclusions from the research.

2.1 Introduction

Global climate change is one of the most complex challenges facing people in the twenty-first century. To fulfill the commitments of the "Kyoto Protocol" at as low a cost as possible, the European Union Emissions Trading Scheme (EU ETS) was established by EU Directive 2003/87/EC in 2003 and started in January 2005. The EU ETS set CO_2 emissions upper limits for 12,000 emission facilities, such as generator sets, oil refining equipments, building materials, paper-making equipments, and metal manufacturing equipments, across 25 EU member states. The EU ETS can be divided into four phases: Phase I (2005–2007), Phase II (2008–2012), Phase III (2013–2020), and Phase IV (2021–2028). After years of rapid development, the EU ETS has gradually developed into a financial market covering carbon spot, futures, options, and other trading products. Whether in market value or trading volume, the EU ETS is currently the world's largest carbon market. Its value is much higher than other major global carbon markets, and also significantly exceeds the clean development mechanism (CDM) carbon market. Moreover, the EU ETS is a weather vane for global carbon market trading. Its development shapes the direction of global carbon market, and its market situation directly affects the reference prices for global CO_2 trading (Zhang and Wei 2010). In recent years, the EU ETS has become an important tool as mankind tries to cope with climate change, as well as a major choice for investors diversifying their investment risks. Therefore, the issues surrounding carbon market and carbon finance have become foci for energy and climate change researchers (Wei et al. 2010).

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In recent years, more and more researchers around the world began to pay attention to the EU ETS carbon market. Considering the environmental benefit and cost-efficiency of this EU ETS carbon market, many researchers have studied its Phase I to date, although this phase is, in essence, a learning phase. For instance, Mansanet-Bataller and Pardo (2007) and Alberola et al. (2008, 2009) inspected the driving factors of 2005–2007 carbon prices successively. Paolella and Taschini (2007), Daskalakis (2008), Seifert et al. (2008), Benz and Truck (2009) explored the carbon price behaviors in Phase I for prediction. However, only a few researchers, such as Feng et al. (2011), Chevallier (2012), and Creti et al. (2012) studied the drivers of carbon prices in Phase II.

Existing research results can provide this study with important references. However, they also show some disadvantages. First, existing studies mainly focus on the EU ETS Phase I. Since the market experiences, market characteristics (mobility and depth), and market rules of Phase II differ from those of Phase I, the results of Phase I may not apply to Phase II, particularly the driving factors used in testing carbon prices. Second, existing results are basically obtained from carbon spot prices. At present, carbon spot trading is still very low, while carbon futures trading are the main product in carbon markets. Besides, carbon futures contracts can also yield higher research value (World Bank 2012). However, carbon futures price studies are rare. Since carbon futures enjoy greater trading volume than carbon spot price trades theoretically, carbon futures prices are much less sensitive to the important structural changes that have occurred on the spot market during the study period—January 2006 to April 2012. Thus, carbon futures prices show more steady fluctuation than spot price equivalents. Thereby, the research conclusions from carbon spot prices are probably not applicable to carbon futures prices. This situation is not beneficial when trying to grasp a general view of the driving factors of carbon prices and cannot provide investment decision-makers with enough information supports. Third, existing studies mainly employ traditional multiple linear regression method. This method can basically cause multicollinearity in existing results. Therefore, the reliability of research results is low, and the driving factors of carbon prices cannot be effectively grasped. In summary, although the EU ETS has attracted the attention of researchers for several years, its study is still in the initial stage.

This study is designed to explore the driving factors of carbon futures price over the Phase I and Phase II–January 2006 to April 2012. Being similar to the study by Creti et al. (2012), we use the cointegration techniques to identify the determinants of the carbon price over the whole study period. This study extends the study of Creti et al. (2012) in two aspects: first, more driving factors are considered in this study, i.e., energy prices are imported with crude oil price, as well as coal, gas, and electricity prices; besides temperature conditions, economic activities and institutional decisions which intensively influence the EU ETS carbon market, are introduced into determine the driving forces of carbon futures price. As far as we know, the influences of 2007s Bali action plan, 2008s global financial crisis, and 2011s European debt crisis on the EU ETS carbon market have not been empirically analyzed. Thus, in this chapter, we seek to measure the time-points of structural changes of carbon price series probably caused by these events using the BP structure breakpoint test algorithm proposed by Bai and Perron (2003). Furthermore, these time-points are included amongst the driving factors. Second, to eliminate multicollinearity among the independent variables to obtain more reliable regressive results, the ridge regression method is used to deduce the equilibrium carbon price and reveal the main reasons for the difference between the equilibrium carbon price and the observed carbon price.

Our results show that 2007s Bali action plan, 2008s global financial crisis, and 2011s European debt crisis all exerted significant influences on carbon prices. Each influence leads to a structural breakpoint of carbon price; meanwhile, a long-term cointegration relationship existed between carbon price and its driving factors including energy prices, weather conditions, economic activities and institutional decisions; equilibrium values show that the observed carbon price has been lower than its equilibrium value since October 2009, and carbon price still tends to be depreciated in the future.

2.2 Carbon Price Drivers

Key factors such as energy prices, weather conditions, economic activities, and institutional decisions can exert significant impacts on carbon price (Alberola et al. 2008).

Energy prices exert obvious influences on carbon price. Since fossil energy consumption is the main source of CO_2 emissions, power enterprises can switch within various fossil fuels-coal, natural gas, or oil. Thus an internal price transmission mechanism is induced between fossil energy and carbon markets. Carbon price is thus closely connected to energy prices. The rising in energy prices will induce the rise of carbon price, while energy prices fall will also cause decreased carbon price. This idea is supported by Kanen (2006), Convery and Redmond (2007), Mansanet-Bataller and Pardo (2007), Oberndorfer (2009), Hintermann (2010), Mansanet-Bataller et al. (2011).

Carbon market is a temperature-sensitive market, so temperature conditions significantly influence carbon price. Since approximately 55% of the EU allowance (EUA) holders are operating in the heat or electricity sectors, in cold and dry winters, more demand for heat, and less output for hydropower can cause the shortage of EUA and rising carbon price; in hot and dry summers, the surge in electricity demand causes a shortage of hydropower resources. Meanwhile, nuclear power is frequently maintained due to high temperatures. Therefore, electricity supplies rely on coal, resulting in the growth of CO_2 emissions and their cost. This idea is supported and checked by Mansanet-Bataller and Pardo (2007), Alberola et al. (2008), Daskalakis 2008), Benz and Truck (2009), Hintermann (2010), Wei et al. (2010).

Economic activities show obvious influences on carbon price. Industrial production activities directly determine EUA's supply and demand. An increase in economic activities can draw in more market participants and produce more demands, thus carbon price will rise; conversely, a reduction in economic activities will cause a reduction in the number of market participants: demand and carbon price thus fall. Seifert et al. (2008), Hintermann (2010), Chevallier (2012) support and validate this idea.

Institutional decisions exert significant influences over carbon price. As a policy product of CO_2 emissions reduction protocols for EU member states, carbon price is affected by market mechanisms as well as external heterogeneous environments. Some institutional decisions, such as international climate negotiations, allowance allocation, financial crisis, and important announcements, can influence carbon price and cause large fluctuations therein. For example, due to the influence of certified data leakage event in May 2006, carbon price showed a much larger decrease. The global economic crisis that started in September 2008 caused carbon price to drop from 20 €/t to 15 €/t. Economic recession greatly dampens demand, thus output reduces and demand for EUA substantially decrease, resulting in the increase of carbon market supply, demand reduction, and subsequently lower carbon price. This conclusion is well supported by Christiansen et al. (2005), Zachmann and von Hirschhausen (2008), Alberola et al. (2009), Chevallier et al. (2009), Mansanet-Bataller et al. (2011).

Owing to its variations over different EU ETS phases, carbon price presents complex relationships with energy prices, weather conditions, economic activities, institutional decisions, and other factors. Wei et al. (2010) examined the long-term and short-term interactions between the EU ETS carbon price and energy prices using cointegration techniques. The results showed that energy prices displayed a weak relationship with carbon futures price in Phase I, but presented a long-term equilibrium relationship with carbon futures price in Phase II. Energy prices variations were also an important cause behind carbon price changing in Phase II. Keppler and Mansanet-Bataller (2010) studied the relationship of carbon price and energy prices using Granger causality test method. They found that in Phase I carbon price was affected by coal and natural gas prices, then carbon price influenced electricity price; in Phase II, natural gas was still an important factor influencing carbon price, but coal price no longer influenced carbon price, and carbon price was also no longer a factor influencing electricity price. On the contrary, electricity price influenced carbon price; stock price was transformed from an energy price-follower in Phase I to a price-driver in Phase II; weather conditions showed important influences on carbon price in both Phases I and II. Mansanet-Bataller et al. (2011) found that energy prices were the main driving force in Phase II using their TGARCH model, while economic activities and temperature conditions were no longer significant factors. This conclusion was different from that of Phase I. Guebrandsdóttir and Haraldsson (2011) found that certified emissions reductions (CERs) price could well predict EUA price, and electricity price did not significantly affect EUA price when studying carbon price prediction. Creti et al. (2012) compared carbon price driving factors of Phases I and II by cointegration techniques. They concluded that there were different long-term cointegration relationships between carbon price and energy prices of the two phases considering 2006s structural breakpoint.

2.3 Data

2.3.1 Carbon Price

The European Climate Exchange (ECX) is the largest carbon exchange in the EU ETS system. The daily carbon trading volume of this exchange accounts for more than 80% of the total carbon trading amount of the EU's main carbon exchanges. Therefore, its trading position largely reflects general trends in EU ETS carbon trading. This chapter selected monthly price data for EUA carbon futures contract matured in December 2012, namely DEC12, over the period January 2006 to April 2012. With €/t CO_2 as its unit, a total of 76 monthly data points was used: the carbon price was denoted by *Carbon*.

2.3.2 Energy Prices

The selected energy prices from January 2006 to April 2012 are indicated as follows: (1) oil price; ICE (intercontinental exchange) monthly Brent oil price was used in units of U.S. dollars per barrel, and denoted by Brent; (2) coal price; The monthly coal futures contract price at three influential harbors (Amsterdam, Rotterdam, and Antwerp) on the European Energy Exchange (EEX), located in Germany, was applied in units of €/t, and was denoted by Coal; (3) natural gas price. Since UK is the biggest natural gas consumer in the EU, ICE natural gas price movements basically shape the condition of the European natural gas market. Thus, the ICE monthly British Gas futures index price was used in this chapter in pence/British thermal unit (BTU), and was denoted by Gas; (4) electricity price; Germany's installed capacity and power generation rank first in Europe and Germany has the EU's largest electricity market. Thus, we selected the EEX electricity futures price, in units of €/MWH which was denoted by *Elec*.

2.3.3 Temperature Conditions

Tendances Carbone's EU temperature index monthly mean was used and denoted by *Temp*.

2.3.4 Economic Activities

Tendances Carbone's Europe industrial production index (seasonally adjusted) was introduced to reflect general European economic activities, and was denoted by *Indu*. The data selected in this chapter are presented in Table 2.1.

2.3.5 Institutional Decisions

To explore the structural changes in carbon price series, the time-points of structural changes therein were measured using global minimisation of the absolute sum of squared residuals (SSR) in the BP structure breakpoint test algorithm proposed by Bai and Perron (2003). Assuming that there are m breakpoints, the corresponding model is given by formula (2.1)

$$\begin{aligned} y_t &= x_t' \beta + z_t' \delta_1 + u_t, t = 1, 2, \ldots, T_1 \\ y_t &= x_t' \beta + z_t' \delta_2 + u_t, t = T_1 + 1, T_1 + 2, \ldots, T_2 \\ y_t &= x_t' \beta + z_t' \delta_{m+1} + u_t, t = T_m + 1, T_m + 2, \ldots, T. \end{aligned} \tag{2.1}$$

where y_t is the value of the dependent variable at t, $x_t(p \times 1)$ and $z_t(p \times 1)$ are covariance vectors, β, δ_j, $j = 1, 2, \ldots, m + 1$ are corresponding coefficient vectors; u_t is a random disturbance term, and $(T_1, T_2, \ldots, T_m)$ are breakpoints. Then calculate the minimum SSR values after one, two, and m structural change times within the sampling period respectively. Finally, Bayesian information criteria (BIC) were used to find the number of optimal breakpoints and each breakpoint's occurrence time.

Three breakpoints were found by this breakpoint test: September 2007, October 2008, and May 2011. These three breakpoints caused one surge, and two slumps, in carbon price, as shown in Figs. 2.1 and 2.2. Every surge and slump in carbon price is closely connected with institutional decisions. The first surge in the carbon price

Table 2.1 Descriptive statistics

	Mean	Range	Maximum	Minimum	Standard deviation	Skewness	Kurtosis
Carbon	18.46	23.73	30.82	7.09	5.82	0.22	−0.42
Brent	83.69	92.23	135.73	43.50	23.35	0.41	−0.81
Gas	5.72	6.97	9.45	2.48	2.01	−0.04	−1.35
Coal	76.72	90.59	135.56	44.97	27.99	0.64	−1.04
Elec	53.25	81.09	109.40	28.31	15.60	0.98	1.54
Temp	11.20	22.50	22.90	0.40	6.03	−0.02	−1.20
Indu	103.51	24.20	114.00	89.80	7.36	−0.40	−0.94

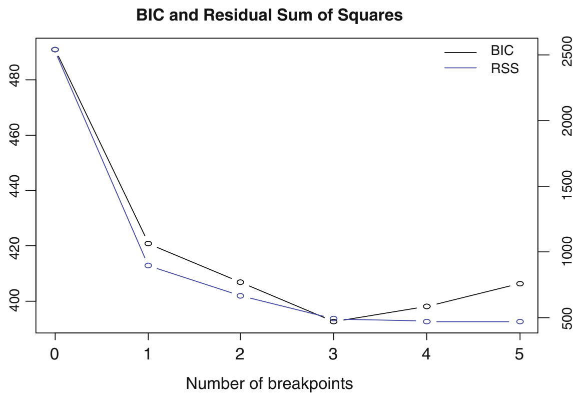

Fig. 2.1 Number of carbon price BP breakpoints (January 2006 to April 2012)

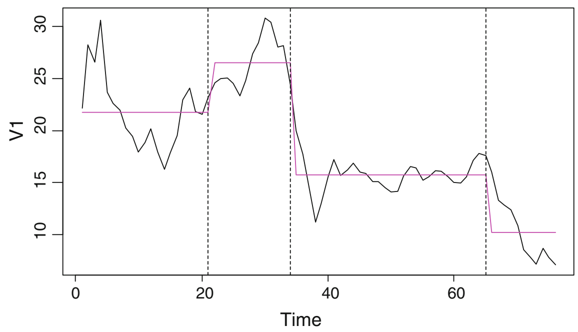

Fig. 2.2 Time-points of carbon price BP breakpoints (January 2006 to April 2012)

was derived from the implementation of more stringent emissions reduction policy announced by both globally and EU-wide. The first slump in the carbon price originated from the global financial crisis. The second slump was caused by the European debt crisis. Therefore, three dummy variables were introduced in this chapter to shape the impacts of these institutional decisions on the carbon market. The institutional decisions before, including, and after September 2007 were taken as 0 and 1 respectively and were denoted by Break1; those before, including, and after October 2008 were taken as 0 and 1 respectively, and were denoted by Break2; those before, including, and after May 2011 were taken as 0 and 1 respectively, and were denoted by Break3.

2.4 Cointegration Test and Ridge Regression Results

2.4.1 Cointegration Test

In this chapter, cointegration techniques were used to identify the potential long-term equilibrium relationship between carbon price and its driving factors.

Table 2.2 Unit root testing results

	ADF value	*p*-value		ADF value	*p*-value
Carbon	−1.518578	0.5188	ΔCarbon	−8.024510	0.0000***
Brent	−2.760113	0.0691*	ΔBrent	−4.908595	0.0001***
Gas	−2.153741	0.2248	ΔGas	−8.228513	0.0000***
Coal	−1.883104	0.3384	ΔCoal	−5.645959	0.0000***
Elec	−3.743625	0.0052***			
Temp	−9.484851	0.0000***			
Indu	−1.733334	0.4104	ΔIndu	−3.655754	0.0068***

Δ indicates first-order difference. ***(resp. **,*) indicates the rejection of the null hypothesis of a unit root at the 1% (resp. 5, 10%) significance level

First, the Augmented Dickey–Fuller (ADF) unit root test was applied to test the stability of those variables studied.

It can be observed from Table 2.2 that, except for several series such as oil price, electricity price and temperature condition were steady at the 10% significance level, the remaining series were first-order steady. According to econometric theory, it can be considered that all series were first-order steady. Therefore, a multiple linear regression model concerning carbon price and energy prices, temperature condition, economic activity and institutional decisions, can be obtained as formula (2.2)

$$\begin{aligned} Carbon_t = \beta_0 + \beta_1 Brent_t + \beta_2 Coal_t + \beta_3 Gas_t + \beta_4 Elec_t + \beta_5 Temp_t + \beta_6 Indu_t \\ + \beta_7 Break1_t + \beta_8 Break2_t + \beta_9 Break3_t + \varepsilon_t, \end{aligned} \tag{2.2}$$

where t refers to month t in the study period, and ε is an error term.

Second, Johansen's cointegration techniques were used to determine whether or not the multiple linear regression models above could be regarded as a long-term equilibrium relationship. Test results are shown in Table 2.3 which suggested that carbon price and its driving factors reject the null hypothesis containing no

Table 2.3 Johansen's cointegration trace test results (*p*-value)

Null hypothesis	Trace Statistic	Prob.**
None*	393.5157	0.0000*
At most 1*	283.1781	0.0000*
At most 2*	213.7940	0.0000*
At most 3*	149.1962	0.0008*
At most 4*	100.0302	0.0246*
At most 5	64.02284	0.1329

Trace test indicates 5 cointegration eqn(s) at the 0.05 level
*Denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) *p*-values

cointegration relationship at the 5% significance level. This finding was in accordance with that by Creti et al. (2012) and the results from their study of Phase II by Bredin and Muckley (2011). However, it differed from that of Phase I by Bredin and Muckley (2011), in that, when the structural change in the carbon price series caused by the certified data leakage event in May 2006 was not considered, cointegration relationship did not exist in carbon price and its driving factors. The reason is possibly that Phase I of the EU ETS, as a highly uncertain emerging future market, may just have been a short trial period; when the structural change of carbon price series caused by the aforementioned May 2006 events were considered, a cointegration relationship reappeared between carbon price and its driving factors. This finding proved the conclusions matched those of Gregory et al. (1996): structural changes in time series were the preference of cointegration test, resulting in the error that: "the null hypothesis that should be rejected is denied due to the structural changes".

2.4.2 Ridge Regression Estimation

Based on Johansen's cointegration test results, the cointegration relationship between carbon price and its driving factors was estimated. First, the correlation between variables was evaluated by multicollinearity test: the results are shown in Table 2.4 where a strong significant correlation may be seen between some variables. Thus, it can be deduced that the correlation between some of the variables are strong and that there may be significant multicollinearity.

Second, ordinary least squares (OLS) estimation was introduced to further check whether or not there was multicollinearity. The OLS estimation results are shown in Table 2.5 which shows that OLS coefficients displayed extreme value phenomenon. Some coefficients were highly significant, while others were insignificant. Moreover, R square and the F-statistic indicated higher regression significance. Thus, it can be judged that multicollinearity was possibly present. Some inflation factors (VIFs) of independent variables were greater than 5, even 10, indicating that there was severe multicollinearity between variables. Due to the presence of this severe multicollinearity, the OLS estimation coefficients cannot be guaranteed to have been reliable. Therefore, the OLS estimation results cannot be used to conduct analysis and exercise judgement thereon. Only by eliminating this multicollinearity between the independent variables, can robust regression results be obtained.

Third, to overcome this multicollinearity between independent variables to obtain robust regression results, ridge regression was used to conduct model estimation. Ridge regression is a biased estimation regression method for data analysis in the face of multicollinearity: it is actually modified from OLS. It is a regression equation obtained by abandoning the non-biased nature of OLS, while sacrificing

Table 2.4 Correlation test results

	Carbon	Brent	Gas	Coal	Elec	Temp	Indu	Break1	Break2	Break3
Carbon	–	–								
Brent	−0.030	–								
Gas	0.041	0.673^{**}	–							
Coal	−0.067	0.878^{**}	0.806^{**}	–						
Elec	0.438^{**}	0.242^{*}	0.593^{**}	0.386^{**}	–					
Temp	0.239^{*}	0.098	−0.139	0.026	−0.178	–				
Indu	0.625^{**}	0.279^{*}	0.391^{**}	0.284^{*}	0.339^{**}	0.090	–			
Break1	-0.336^{**}	0.453^{**}	0.373^{**}	0.521^{**}	0.214	−0.129	-0.424^{**}	–		
Break2	-0.774^{**}	0.103	0.038	0.199	−0.177	−0.155	-0.805^{**}	0.682^{**}	–	
Break3	-0.570^{**}	0.567^{**}	0.451^{**}	0.577^{**}	−0.068	−0.012	−0.053	0.259^{*}	0.379^{**}	–

**(resp. *) is significant at the 5% (resp. 10%) level (2-tailed)

Table 2.5 Ordinary least squares estimation results

	Unstandardized coefficients	*t*-Statistic	Sig.	VIF
C	16.821	1.512	0.135	
Brent	0.022	0.777	0.440	5.650
Gas	−0.281	−0.947	0.347	4.622
Coal	0.035	1.100	0.275	10.173
Elec	0.111	4.222	0.000*	2.184
Temp	0.165	3.313	0.002*	1.184
Indu	−0.041	−0.387	0.700	7.983
Break1	0.952	0.777	0.440	3.841
Break2	−7.769	−4.690	0.000*	8.912
Break3	−6.658	−5.635	0.000*	2.454
R Square	0.922			
F-Statistic	41.832			
Sig.	0.000			

*Is significant at the 1% level (2-tailed)

some information and accuracy, yet providing a regression coefficient more suitable for practical application. The residual standard deviation of a ridge regression is larger than that of an OLS regression, but it presents much stronger stability and pathological tolerance compared to OLS. The Gauss–Markov theorem indicates that multicollinearity does not affect estimators and minimum variance of an OLS. Though OLS estimation shows the minimum variance in all linear unbiased estimations, this minimum variance is not necessarily small. In fact, a biased estimation can be applied. Though a biased estimation may show a slight deviation, its accuracy is much higher than the unbiased estimation. Based on this principle, ridge regression estimation is obtained by introducing biased constants in the normal equations. Ridge regression is defined as $\beta(k) = (X'X + kI)^{-1}X'Y$. Where, X is the independent variable matrix, X' is the transpose of X, Y is dependent variable vector, k is the ridge parameter or biased parameter, usually such that $0 < k < 1$, and $\beta(k)$ is the ridge regression estimator of regression coefficients vector. When $X(t)$, ridge regression is reduced to OLS regression (Hoerl and Kennard 1970).

By observing the ridge tracks and changing tendency of ridge regression's estimated R square with k, the acquired regression coefficients of independent variables were more stabilized when $k = 0.10$. Therefore, $k = 0.10$ was selected for this ridge regression estimation: key results are shown in Table 2.6 where it can be seen that the ridge regression coefficients of most variables are significant at 10%, or even 5 and 1% levels. Meanwhile, R square reached 0.917, which indicated that the overall fit was good. Besides, the F-statistic passed the 1% significance level test, and the VIF of each independent variable was obviously less than 5. Therefore,

Table 2.6 Ridge regression estimation results ($k = 0.10$)

	Unstandardized coefficients	*t*-Statistic	Sig.	VIF
C	2.730857	0.560471	0.288528	
Brent	0.024816	1.578961	0.059563*	1.650
Gas	−0.185543	−0.986962	0.163633	1.747
Coal	0.008783	0.645156	0.260531	1.778
Elec	0.105719	5.261444	0.000001***	1.204
Temp	0.166533	3.719303	0.000207***	0.893
Indu	0.097748	2.023594	0.023532**	1.546
Break1	0.478986	0.599370	0.275489	1.537
Break2	−5.187872	−7.255254	0.000000***	1.559
Break3	−6.278589	−7.143728	0.000000***	1.275
R Square	0.917			
F-Statistic	38.824			
Sig.	0.000			

***(resp. ***, **) is significant at the 1% (resp. 5, 10%) level (2-tailed)

each variable regression coefficient was basically in line with economic tests, and the overall model fitting effect was consistent with the prevailing EU ETS carbon market trading situation and its price driving mechanism.

2.4.3 Granger Causality Test

Based on the estimation results obtained above, Granger causality test results are shown in Table 2.7. The results showed that, over the whole period, carbon price was affected by energy (oil, gas, coal, and electricity) prices, as well as economic activities and institutional decisions (Break2 and Break3) in either the short, or long terms. The short-term or long-term impacts of institutional decision (Break1) and temperature condition on carbon price were not obvious. The results verified the relevant conclusions by Alberola et al. (2008), Keppler and Mansanet-Bataller (2010), Mansanet-Bataller et al. (2011), Creti et al. (2012). Meanwhile, it provided a stronger economic basis for these studies. Another interesting feature was that carbon price can generate short-term and long-term impacts on oil, gas, and electricity prices. This meant that the barriers between the EU ETS carbon market and energy markets such as those for oil, natural gas, and electricity, have been gradually eliminated by the information transmission mechanism. Therefore, various market prices present an incipient interaction, which enhances the status and role of carbon market in the macro-economy system.

Table 2.7 Granger causality test results (p-value)

	Carbon	Brent	Gas	Coal	Elec	Temp	Indu	Break1	Break2	Break3
Carbon	–	0.0651*	0.0829*	0.2231	0.0578*	0.2780	0.4361	0.9924	0.3954	0.8259
Brent	0.0142**	–	0.0002	0.0005	0.0232	0.4023	0.0055	0.7675	0.0173	0.0689
Gas	0.0184**	0.7633	–	0.8914	0.2987	0.1330	0.1891	0.9821	0.0700	0.2685
Coal	0.0371**	0.9523	0.0015	–	0.0775	0.3950	0.0208	0.7820	0.0800	0.0342
Elec	0.0095***	0.1445	0.2313	0.2605	–	0.1422	0.0798	0.4712	0.0074	0.9912
Temp	0.2920	0.1137	0.7453	0.4171	0.0309	–	0.6151	0.5437	0.3018	0.2427
Indu	0.0701*	0.9391	0.1148	0.7933	0.1163	0.9553	–	0.7096	0.4044	0.9996
Break1	0.5361	0.6092	0.2409	0.3691	0.0608	0.5496	0.1921	–	0.1486	0.7712
Break2	0.0182**	0.2902	0.2913	0.2183	0.0043	0.5287	0.0482	1.0000	–	0.5392
Break3	0.0677*	0.2465	0.4957	0.8579	0.6897	0.5236	0.9410	1.0000	1.0000	–

Note The test is based on the null hypothesis that the variable X in line does not cause the variable Y in column. *** (resp. **,*) indicates the rejection of the null hypothesis of no causality at the 1% (resp. 5, 10%) significance level. The p-values in parentheses are relating to short-run causality, the other reported p-values correspond to long-run causality

2.5 Equilibrium Carbon Price

2.5.1 Equilibrium Carbon Price Equation

According to the cointegration relationship between carbon price and its driving factors obtained above, the corresponding equilibrium carbon price can be deduced. Relying on the ridge regression estimation results, the equilibrium carbon price can be expressed as formula (2.3)

$$\begin{aligned}\mathrm{Carbon}_t = {} & 2.7309 + 0.0248\,\mathrm{Brent}_t - 0.1855\beta_2\,\mathrm{Coal}_t + 0.0088\,\mathrm{Gas}_t + 0.1057\,\mathrm{Elec}_t + 0.1665\,\mathrm{Temp}_t \\ & + 0.0977\,\mathrm{Indu}_t + 0.4790\,\mathrm{Break1}_t - 5.1879\,\mathrm{Break2}_t - 6.2786\,\mathrm{Break3}_t\end{aligned} \tag{2.3}$$

Natural gas and coal prices coefficients were not significant at the 10% level. This result contradicted Alberola et al. (2008), Keppler and Mansanet-Bataller (2010) and Chevallier (2012) who believed that changes in carbon price were derived from those of natural gas and coal prices. The reason for this contradiction may have been that: (1) Alberola et al. (2008) used OLS to analyze the driving factors of carbon spot price in Phase I, thus there may be multicollinearity. (2) This may explain that there are some barriers in the internal transmission mechanism, in particular, that of information, between carbon market and energy markets for natural gas, coal, etc. The information transmission between these two markets is not smooth enough. We have reasons to believe that with the gradual improvement of carbon market, natural gas, and coal prices would significantly affect carbon price.

First, of those significant energy prices, oil and electricity prices showed positive effects on carbon price. Electricity price coefficient was positive and significant at the 1% level. The power generation facilities of EU states are restricted due to a general lack of water resources. In EU member states, especially Germany, coal is used extensively for power generation to meet the demand for electricity. Large amounts of coal consumption will lead to increased CO_2 emissions, followed by an increased CO_2 allowance. Therefore, large power plants invoke the most important CO_2 emissions allowance demands. Electricity price rises with increased power generation cost mainly caused by the rising costs of coal and natural gas, carbon price is thereby increased. Oil price manifests a positive effect on carbon price. Specifically, when oil price rises, people tend to use relatively cheaper coal, thus more CO_2 is emitted and more CO_2 emissions allowance is needed, promoting the increase of carbon price; when oil price falls, people will generally reduce their use of coal since oil is cleaner than coal due to the lower CO_2 emissions coefficient of oil, meanwhile CO_2 emitted is reduced, and carbon price is thereby lowered.

Second, temperature condition showed positive effects on carbon price. Temperature condition coefficient was positive and significant at the 1% level. This ran contrary to the conclusions of Alberola et al. (2008) and Mansanet-Bataller et al. (2011). They considered that the temperature condition did not significantly influence carbon price, the reason may be that: (1) Temperature condition shows a nonlinear, rather than a linear, effect on carbon price. (2) Seasonal factors show more effects on carbon price than temperature condition. In theory, climate deterioration or extreme weather events' occurrence can exert entity impacts on carbon-regulated industries. These impacts are indirect and complex. In cold and dry winters, or in hot and dry summers, electricity demand surges. The increase in coal consumption can cause increasing CO_2 emissions, which promotes an increased carbon price. Moreover, drought affects hydropower generation to some extent and coal consumption will thence increase, leading to increasing CO_2 emissions and subsequent carbon price rises.

Third, economic activity showed positive effects on carbon price. Economic activity coefficient was positive and significant at the 1% level. This result was consistent with the conclusion of Creti et al. (2012), namely, economic activity showed significantly positive effects on carbon price, while it differed from the conclusion by Mansanet-Bataller et al. (2011). They argued that economic activity could not show positive effects on carbon price. The improvement of macro-economic situation will induce expansion of industrial production, which creates new demands for energy consumption such as electricity, coal, etc., and especially increases demand in high energy-consuming industries such as non-ferrous metallurgy, chemical, electrical, etc. These demands can enlarge the uptake of various energy sources, leading to increased CO_2 emissions. In the event of certain national emissions reduction allowances, new demand for CO_2 emissions allowances will be created to offset increasing CO_2 emissions arising from industrial production increases. Finally, carbon price increases are promoted. Otherwise, when macro-economic effects present a downtrend, energy consumptions will also come down significantly, resulting in the reduction of CO_2 emissions and an eventual carbon price drops.

Fourth, of those three structural breakpoints, the first (Break1) was not significant at the 10% level, while the following two (Break2 and Break3) showed negative impacts on carbon price, and were both significant at the 1% level. This result was inconsistent with the conclusions of Chevallier et al. (2009) who found that the certified information leakage event occurred in May 2006 significantly affected carbon price. The main reason may be that they used carbon spot price in Phase I, while we used the mixed carbon futures price of Phases I and II. BP structure breakpoint test results showed that this event did not cause structural changes in carbon price. The global financial crisis in 2008 and Europe's debt crisis in 2011 exerted stronger influences on carbon price than Bali Action Plan in 2007. The former two caused declining carbon price with an average amplitude of −5.1879 €/t and −6.2786 €/t respectively, which were both higher than the rising average amplitude of 0.4790 €/t caused by the latter. This may be the main reason that the former two were significant throughout the period, while the latter was insignificant.

2.5.2 Comparison of Observed Carbon Price and Equilibrium Carbon Price

To analyze whether or not the observed values over the whole period lay close to corresponding equilibrium values, we calculated the difference between the observed carbon price and equilibrium carbon price to reveal the carbon market price formation mechanism and stress the importance of carbon price prediction.

The observed and equilibrium carbon prices are shown in Fig. 2.3. The corresponding deviations are shown in Fig. 2.4. In general, the deviations were smaller, and the relative error concentrated to within 10%. However, those deviations in April 2006, October 2006, February 2007, May 2011, and November 2011 were much larger, with relative errors greater than 20%: in particular, in April 2012, it even approached 40%.

The appreciation defined in this chapter refers to the fact that the observed value is higher than its equilibrium value. Otherwise, it will represent depreciation. Thus it can be seen that appreciation and depreciation periods appeared alternately with carbon price changes from January 2006 to April 2012.

The first appreciation period occurred in the first half of 2006. During this period, the increase in energy prices and CO_2 emissions predictions, as well as traders' high expectations for carbon price, trigged carbon price inflation. If carbon price was determined by the balance of market supply and demand, it should not have reached such a high level. In fact, rising energy prices encouraged companies to substitute natural gas for coal to reduce CO_2 emissions. Therefore, carbon price fell.

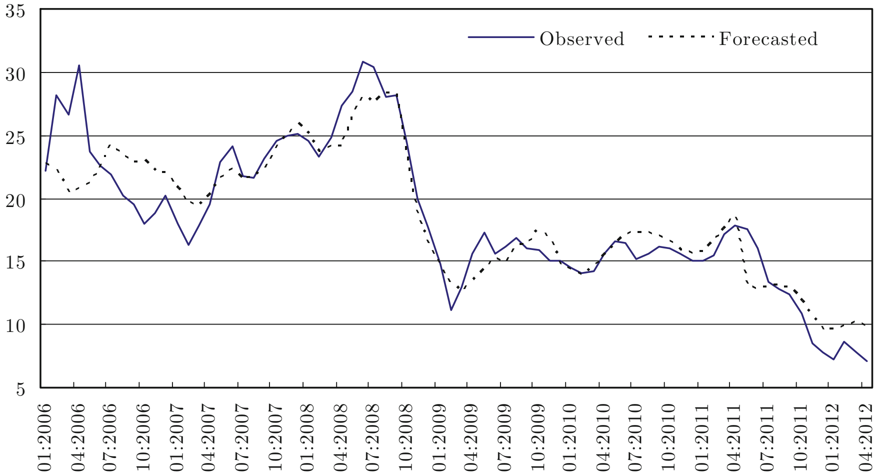

Fig. 2.3 Observed and equilibrium carbon prices

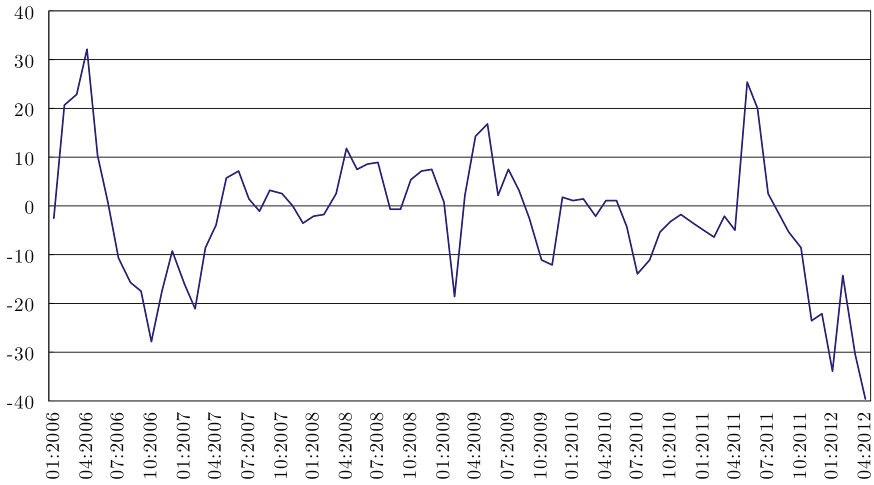

Fig. 2.4 Relative error between observed and equilibrium carbon prices

The first depreciation period occurred in the second half of 2006. Affected by the certified information leakage event occurred in May 2006, and EUA over-allocation up to 37 Mt announced by EU, carbon price plummeted from more than 30 €/t to 20 €/t.

The second appreciation period occurred in the summer of 2007. In this period, oil price played a key role in the rising carbon price. In fact, due to the shortages of global crude oil supply caused in part by tensions in Nigeria and limitations in the United States' ability to supply gasoline, oil price showed an upward trend which, in turn, pushed up carbon price, whereas carbon price was not sensitive to natural gas price reductions. Furthermore, in March 2007, the European Parliament announced that EU ETS would continue until 2020, which increased carbon futures price. Therefore, the observed and equilibrium values were all subjected to stimulated increase.

The second depreciation period occurred towards the end of Phase I when the carbon price fell due to its EUA being non-banking-EUA in Phase I was no longer suitable in Phase II. This decline had nothing to do with changes in underlying energy prices.

The third appreciation period occurred from January 2008 to August 2009, except for a downturn in the winter of 2009. Due to a declining carbon spot price, large amounts of carbon trading were transferred to carbon futures market. In addition, fine market expectation resulted in rising pressures on carbon price. In fact, in the first half of 2008, carbon futures market trading volumes accounted for more than 80% of the total trading volume. Moreover, the rise in oil price also played a key role in carbon price rise. During that period, with a shortage of global oil supply, oil price jumped to $147 per barrel, which was then its highest point in history. The rise in oil price pushed up carbon price. Then in October 2008, the onset of global financial crisis caused the depression in industrial production and the lack of market demand, which made the sharp decline in carbon price. At the beginning of 2009, carbon price fell below their equilibrium values. Then due to EU stimulations such as taking some effective measures, carbon market gradually recovered, and carbon price returned to, or exceeded, its equilibrium value.

The third depreciation period appeared after August 2009. With global financial crisis spreading to Europe, debt crisis was induced in Europe by the end of 2009. Some countries faced bankruptcy, industrial production activities stagnated and governments had no time to formulate, let alone implement, policies to address climate change. Moreover, with 2013 approaching and uncertain prospects looming in post-Kyoto times, carbon market expectations were gloomy, resulting in falling carbon price. At present, carbon price is still depreciating.

2.6 Conclusion

Based on the monthly EU ETS carbon futures price data, we investigated the driving factors behind carbon price using structure breakpoint tests, cointegration techniques, and ridge regression method. The following conclusions can be drawn.

First, 2007s Bali action plan, 2008s global financial crisis, and 2011s European debt crisis exerted significant influences over carbon price and caused the generation of structure breakpoints therein.

Second, a cointegration relationship existed between carbon price and its driving factors including energy prices, weather conditions, economic activities, and institutional decisions.

Third, equilibrium values showed that the observed carbon price had been lower than its equilibrium values since October 2009. Carbon price still tends to future depreciation.

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