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Long-Term Carbon Credit Dynamics on the EU ETS

Folmer Ferment

321676

supervised by

H.J.W.G. Kole

Co-reader

D.J.C. van Dijk

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Abstract

This thesis studies the long-term price dynamics of the EU Emission Allowances (EUAs) and Certified Emission Reductions (CERs), the two carbon credits traded on the EU Emissions Trading Scheme (EU ETS). I use energy, economic, and climate variables and analyse their relationship with the carbon prices in the period April 2009 until December 2014. This thesis models Vector Error Correction Models (VECMs) for the carbon prices and finds that good economic periods, indicated by a high oil price and industrial production, result in an increase of both carbon prices. These promising results show that carbon prices can be meaningfully modelled and have a clear relationship to market securities. VECMs are also shown to perform much better than Vector Autoregressive (VAR) models for the carbon returns. The role of the carbon prices in a VECM diminishes as the number of variables included in the VECM increases. This indicates that although equilibria with carbon prices are present in the market, their effect is easily overshadowed by the relationships between more important variables. Furthermore, this thesis investigates possible structural breaks in the dataset and copes with these by modelling sub-periods and including dummy variables.

1 Introduction

Carbon credits and markets attempt to diminish the world's carbon footprint. The idea is that market mechanisms ensure that society most efficiently allocates emission production. Carbon credits are tradeable certificates representing the right to produce carbon emissions, and can be traded either on carbon market exchanges or over the counter. In 2005 the Kyoto mechanism has been adopted for carbon trading by the European Union. This marked the beginning of large scale carbon trading trough the EU Emissions Trading Scheme (EU ETS). Within the EU ETS a capped number of European Emission Allowances (EUAs) are allocated to the market, initially by free allocation. Industrial producers need these allowances as a right to emit. When industrial producers emit less than the amount of allowances they received, they are able to sell their remaining allowances to producers who emit more. In this manner the market is able to find the most efficient industries to realise emission reductions. Apart from the EU Allowances that are assigned to the market freely or by auction, Certified Emission Reductions (CERs) are also tradeable and used by companies and individuals to offset their carbon footprint. The CERs are issued by the Clean Development Mechanism under the rules of the Kyoto Protocol. Green enterprises can earn these CERs if they have a project that realises emission reductions, and they can monetise them on the international carbon exchanges. Because CERs can partially be used to replace EUAs in offsetting emissions, they perform a similar role in the market.

Carbon price analysis is relevant to many people. Polluting companies, usually industrial producers and electric power companies, are influenced by the costs of offsetting carbon emissions and therefore have interest in the drivers of the carbon price and its predictability. Policy makers have to understand underlying drivers of the carbon price in order to most effectively utilise carbon credits to lower carbon emissions, while not being too restrictive for the economy. And even small companies with projects reducing emissions have a need to understand the carbon markets. These recipients of CERs usually operate some project that is expected to yield carbon credits in the future, but they do not know the expected value associated with these credits. This thesis sheds some light on this. This question is also the motivation of this study as I try to answer it for the NOTS foundation, for which I currently try to make the charcoal market in Sub-Saharan Africa more sustainable.

The EU ETS is introduced in several phases. The specific arrangement of the EU ETS differs over these phases in order for industry and legislators to get used to this new security and to maximise the impact on emission reduction. The first EU ETS trading period lasted from January 2005 until December 2007. The second lasted from January 2008 until December 2012. The third trading period began in January 2013 and will last until December 2020. Because of this division into various stages, constant research is necessary. Chen et al. (2013) demonstrate that the transition between phase I and phase II coincided with a significant break in the carbon prices. This thesis investigates whether or not this also holds for the transition between phase II and III. As the third phase in the EU ETS has now been operating for over three years, a meaningful dataset is available. The main changes in this latest transition are that the default method of credit distribution is now auctioning instead of free allocation, and a single EU-wide cap on emission is put in effect replacing individual national caps.

Since phase II companies are allowed to offset 13.4% of their emissions with CERs. As the EU ETS is the dominant exchange, the CER price has been shown to trail the price of the EUAs. In 2012 the carbon prices collapsed, primarily due to oversaturation of the market. Due to the political nature of the carbon markets, the supply mechanisms of the carbon price will always remain a dominant determinant of the future carbon prices. The main purpose of this thesis is to study if the demand of carbon credits is also significantly influential, and to determine how these prices can

best be modelled, and their relationships can be interpreted, in the long term.
This thesis builds on the existing literature regarding carbon markets. To determine if it is possible to identify some long-term characteristics of the carbon prices I use linear models with economic indicators, energy commodities, climate variables, and exchange rates as explanatory variables. I use a VAR model for difference series and VECMs for the level series. A VECM is particularly useful for modelling cointegrated time series and shedding light on the long-term relationships present in the market.
I find that a VECM outperforms the VAR model. Specifically, I find significant results for a VECM with the two carbon prices, the oil price, and the industrial production index. The equilibrium indicates that a relatively high oil price and industrial production coincides with rising carbon prices. I argue that we can interpret the oil price as an economic indicator, in the sense that a booming economy increases the demand and therefore the price of oil. If this is the case, this long-term relationship shows that the carbon prices are dependent on the economic situation. This is an expected result, as a growing economy should coincide with the need to produce more carbon emissions and therefore raises carbon credit demand. I also estimate two more extensive models: one containing all the energy variables, and one containing all economy variables. These models perform worse compared to the smaller model, and I argue that this is because the relative unimportance of carbon credits causes the VECM to focus on different equilibria between the variables. The results of this thesis are promising, showing that carbon prices can be meaningfully modelled and have a clear relationship to market securities. This thesis is one of the first to study the carbon prices' long-term price dynamics, and they should be further investigated. I suggest doing this by either estimating similar VECMs with a small number of variables, or extending the models with nonlinear specifications.

2 Literature

The body of literature regarding this subject is rapidly growing. Almost exclusively the articles concern the EU ETS, and the carbon allowances in particular; the EU ETS remains the world's largest and most liquid emission trading scheme and the EUAs the most liquid and important security.
Several articles investigate the efficiency and maturity of the carbon market. Hintermann (2010) finds that although the EUA price did not appear to be driven by marginal abatement costs from the start, the inefficiency disappeared over time. Aatola et al. (2014) find profitable trading strategies in the first half of phase II,

demonstrating that there are periods of informational efficiency within the EU ETS. Feng et al. (2011) determine that the carbon price is no random walk, and find short term memory reflected in the carbon price. Fan et al. (2015) study the carbon price from a chaotic viewpoint and find that it can be described as a chaotic phenomenon.
Another important topic has been the structural breaks within the time series. Due to the political nature of the carbon prices and the changes made during the transition between the different phases, structural breaks are expected. Alberola et al. (2008) reveal a first structural break in 2006. Chen et al. (2013) find strong evidence of such a break between the first and the second phase. The large price drop during phase II has been investigated by Koch et al. (2014). They analyse the three most often identified causes of the collapse of the EU ETS carbon price: the economic recession, renewable energy policies and the influx of international credit. The economic recession is indicated as the main cause, while the rise of solar and wind energy also has a small but robust contribution. Due to the political nature of the security, over-allocation is often found to be the cause of a price drop, as in Ellerman and Buchner (2008) and Ellerman et al. (2010). To the best of my knowledge, the transition between phase II and phase III has not yet been sufficiently scrutinized.
As for the drivers of the carbon price, four kinds of variables have been identified: economic indicators, energy commodities, exchange rates, and weather variables. Creti et al. (2012) find that during phase II the role of fundamentals had increased in comparison with the first phase, although they do not investigate weather variables due to expected nonlinearity of the corresponding effects. Chevallier (2010) investigates the transmission of international shocks to the EUA and CER carbon prices, with the use of 115 macroeconomic, financial and commodity variables combined in a FAVAR model, finding that CER prices react much more heavily than allowances do. Chevallier (2011a) and Chevallier (2011c) also model the carbon allowances with Markov switching models, focussing on economic activity and energy prices as fundamental drivers of the carbon prices. Bredin and Muckley (2011) test for cointegration by specifying a VECM, and modify this with a GARCH specification to account for heteroskedastic effects. They conclude that an equilibrium is forming between the EUA price and various types of explanatory variables during the first years of phase II. Koop and Tole (2013) use dynamic model averaging to forecast the European carbon market with macroeconomic explanatory variables. This method is more flexible and allows for changes over time while outperforming conventional regression methods for problems with a large number of predictors.
Another driver of the carbon price is investigated by Yu and Mallory (2014), who study the impact of currency exchange rates on the carbon market. Interestingly,

the USD/EUR exchange rate is thought to have two opposing effects on the carbon price: on the one hand through substitution of energy sources and on the other hand through the effect on the economy through export. They use a structural vector autoregressive model to demonstrate that a shock in the USD/EUR rate impacts the carbon credit market.

Other methods often employed to model the carbon prices are the conditional mean models. This is done by Benz and Truck (2009), who also apply Markov switching models to the EU ETS. They find that both types of models are successful at capturing the EUAs' characteristics such as skewness, excess kurtosis and heteroskedasticity. Chevallier (2011d) finds strong nonlinearities in the conditional mean functions for carbon prices, while the conditional volatility models reveal asymmetric and heteroskedastic behaviour. His forecasting with non-parametric models performs 15% better in prediction error than linear AR models. Alternatively, Fan et al. (2015) use a multilayer perceptron neural network model using k-fold cross validation to provide strong one-step ahead forecasts. Zhu and Wei (2013) also study neural networks and use a hybrid model of autoregressive integrated moving average (ARIMA) and least squares support vector machine (LSSVM) to account for both the linear and nonlinear aspects of the time series respectively. They show that this hybrid model outperforms the singular and other hybrid models when forecasting.

Much research has been done to specifically investigate the behaviour of the carbon price volatility. Byun and Cho (2013) find that forecasting of volatility was most successful using GARCH-type models, comparing these to implied volatility and k-nearest neighbour models. This suggests that options have little information due to their low volume. Chen et al. (2013) reinforce the success of GARCH and the EGARCH(1,1)-t model in particular (compared to other GARCH(1,1) models). Chevallier (2011b) analyses volatility of daily data (using EGARCH), of option prices (using implied volatility), and using intra-day data (using realized volatility). He finds that carbon price volatility is unstable, suggesting that this might be caused by yearly compliance events and uncertainty in post-Kyoto agreements.

The research concerning CERs is very limited. As stated above, Chevallier (2010) finds that CER prices react more heavily to international shocks than EUAs do, and Mansanet-Bataller et al. (2011) study the price relationship between EUAs and CERs, determining that the EUA-CER spread is mainly driven by the EUA prices as the CER price lags that of the EUA.

Various other interesting and tangential carbon studies include Rannou and Barneto (2014) who study the difference between carbon over-the-counter and exchange trading, also using GARCH variants. Daskalakis (2013) uses simple technical analysis and naive forecasts for trading strategies and finds proof for weak market efficiency, indicating the slow maturing of the carbon market. Zhu et al. (2014) use Zipf analysis to model carbon price dynamics and find that carbon price behaviour is asymmetrical (the long-term bearish probability is greater than the long-term bullish probability), while also studying the influence of different types of investors. Finally, Feng et al. (2012) use extreme value theory to measure the risk exposure of the carbon price and determine the Value at Risk of the carbon market, using GARCH to model the volatility and to calculate a dynamic VaR. They find that the downside risk is larger than the upside risk, and that the extreme value theory VaR is much more effective than the traditional method.

The vast majority of these studies are focussed on short-term EUA price and volatility dynamics. Clearly, many questions remain unanswered. This thesis answers a few of these. First, I investigate whether there is a structural break in the carbon prices during the transition of phase II and phase III, similar to the study of Chen et al. (2013) for the transition between phase I and phase II. Second, I build on the existing price modelling literature by investigating the price determinants during the first years of phase III. I diverge from most existing literature by strictly focussing on long-term relationships. Bredin and Muckley (2011) do some initial long-term analysis, using a VECM specification to test for cointegration during the beginning of phase II. They show evidence of an emerging equilibrium in the market. I build on their research by investigating such equilibria for later dates and further shifting the focus to the long-term. I model monthly instead of daily data and investigate the found long-term relationships in detail from both an economic and econometric perspective. Finally, this thesis give special attention not only to the EUAs, but also to the CERs. Like Mansanet-Bataller et al. (2011), I investigate the price relationship between the two carbon series. I diverge by studying them in a broader environment including all other carbon price determinants.

3 Methods

The main purpose of this thesis is to model the long-term price dynamics of carbon credits. I use Vector Autoregressive (VAR) models to link the EAU and CER returns to macroeconomic and other explanatory variables. To determine the long-term equilibria between the various variables, I model the carbon prices using a Vector Error Correction Model (VECM). Because the main purpose of this study is to find the long-term determinants of the carbon price, I do not extend my models to a GARCH variant. Instead, I investigate the possibility of coping with heteroskedastic effects by performing a logarithmic transformation on the data. This section provides a brief overview of the methods employed in this thesis.

3.1 VAR model

Vector Autoregressive (VAR) models are one of the most strong and flexible methods to linearly model multivariate time series (Sims, 1980). VAR models are particularly useful for modelling stationary series, as securities' returns often are.
A *p-th* order VAR, or VAR(p) is defined as follows:

$$\boldsymbol{x}_t = \boldsymbol{c} + \boldsymbol{\Pi}_1 \boldsymbol{x}_{t-1} + \boldsymbol{\Pi}_2 \boldsymbol{x}_{t-2} + ... + \boldsymbol{\Pi}_p \boldsymbol{x}_{t-p} + \boldsymbol{\varepsilon}_t, \qquad t = 1, ..., T \tag{1}$$

where $\boldsymbol{x}_t$ is a $k \times 1$ vector with values of variables at time t, such that $\boldsymbol{x}_{t-1}$ is the first lag of $\boldsymbol{x}_t$, $\boldsymbol{c}$ is the $k \times 1$ vector of constants, $\boldsymbol{\Pi}_i$ is a $k \times k$ matrix of parameters for lag i, and $\boldsymbol{\varepsilon}_t$ is a white noise process.
A VAR model therefore models the dynamics between several variables simultaneously. It is of interest to us not only because we are interested in the influence of the economic, energy, and climate variables on the carbon returns, but also to determine the relationship between the EUA and CER returns themselves.

3.2 VECM

If variables are non-stationary, such that they can move around without returning to a long-term level, a VAR model is insufficient. If this is the case, variables can still be cointegrated with each other. This means that they have a certain long-term equilibrium with one another. If the variables are cointegrated there exists a stationary combination of the variables which can be modelled using a Vector Error Correction Model (VECM) (Enders, 2014). A VECM is simply an extension of a VAR model integrating this stationary combination of the variables to account for their cointegration and therefore their long-run relationship.

3.2.1 Cointegration

Engle and Granger (1987) define cointegration as follows:

The components of the vector $\boldsymbol{x}_t = (\boldsymbol{x}_{1t}, \boldsymbol{x}_{2t}, ..., \boldsymbol{x}_{nt})'$ are said to be cointegrated of order d, b, denoted by $\boldsymbol{x}_t \sim CI(d, b)$ if:

1. *All components of $\boldsymbol{x}_t$ are integrated of order d.*

2. *There exists a vector* $\boldsymbol{\beta} = (\boldsymbol{\beta}_1, \boldsymbol{\beta}_2, ...\boldsymbol{\beta}_n)$ *such that the linear combination* $\boldsymbol{\beta x_t} = \boldsymbol{\beta}_1 \boldsymbol{x}_{1t} + \boldsymbol{\beta}_2 \boldsymbol{x}_{2t} + ... + \boldsymbol{\beta}_n \boldsymbol{x}_{nt}$ *is integrated of order* $(d-b)$ *where* $b > 0$.

The vector $\boldsymbol{\beta}$ is called the cointegrating vector. It is possible that there are multiple stationary linear combinations of the variables, meaning that there is more than one cointegrating vector. The number of cointegrating vectors is called the cointegrating rank.

3.2.2 Error correction

If the variables are cointegrated, they are said to have a long-term equilibrium. The idea is that although in the short term the variables can grow apart, in the long term they will restore the equilibrium and correct for deviations in this relationship. This is called error correction. Error correction can be modelled, and when a VAR is extended in such a way it is called a VECM. This error correction can happen in several ways. Firstly, variables can come nearer to each other to correct for the deviation, by having an opposite response to the deviation. Secondly, the variables can adjust in the same direction but with a different speed, also diminishing the deviation of the equilibrium. Finally, it is possible that some variables do not themselves correct for the equilibrium deviation, but others do. If this is the case, the non correcting variables are called weakly exogenous.
Integrating this error correction into a model, we get the vector error correction model. The VECM for the n-variable case is represented by the following equation:

$$\Delta \boldsymbol{x}_t = \boldsymbol{\pi}_0 + \boldsymbol{\Pi} \boldsymbol{x}_{t-1} + \sum_{i=1}^{p} \boldsymbol{\Pi}_i \Delta \boldsymbol{x}_{t-i} + \boldsymbol{\varepsilon}_t \tag{2}$$

where $\boldsymbol{x}_t$ is the vector of $I(1)$, or non-stationary, variables, $\boldsymbol{\pi}_0$ an $n \times 1$ vector of intercept elements, $\boldsymbol{\Pi}_i$ are $n \times n$ coefficient matrices, $\boldsymbol{\Pi}$ is the error correction coefficient matrix, and $\boldsymbol{\varepsilon}_t$ an $n \times 1$ vector of disturbance terms that may be correlated. If we compare Equation 2 with Equation 1 it is immediately clear that if all element of $\boldsymbol{\Pi}$ are equal to zero the VECM becomes a simple VAR model in differences. The interpretation of the VAR segment in the VECM therefore also remains unaltered, and the VECM is to be seen simply as extending a VAR with an error correction component. Also, because we can rewrite the above equation as:

$$\boldsymbol{\Pi} \boldsymbol{x}_{t-1} = \Delta \boldsymbol{x}_t - \boldsymbol{\pi}_0 - \sum_{i=1}^{p} \boldsymbol{\Pi}_i \Delta \boldsymbol{x}_{t-i} - \boldsymbol{\varepsilon}_t \tag{3}$$

we know that $\boldsymbol{\Pi}$ must contain cointegrating vectors as its rows. This can be deduced from the fact that all right side terms are stationary, as by definition dif-

ferences of $I(1)$ variables are stationary.
More insight can be gained if we do not represent the cointegrating vectors in this manner, however. This can be illustrated in the two variable case:

$$\Delta x_{1,t} = \pi_{10} + \alpha_1(x_{1,t-1} - \beta x_{2,t-1}) + \sum_{i=1}^{p} \pi_{11,i}\Delta x_{2,t-i} + \sum_{i=1}^{p} \pi_{12,i}\Delta x_{1,t-i} + \varepsilon_{1,t} \tag{4}$$

$$\Delta x_{2,t} = \pi_{20} + \alpha_2(x_{1,t-1} - \beta x_{2,t-1}) + \sum_{i=1}^{p} \pi_{21,i}\Delta x_{2,t-i} + \sum_{i=1}^{p} \pi_{22,i}\Delta x_{1,t-i} + \varepsilon_{2,t} \tag{5}$$

where the only difference with the general case is that $\mathbf{\Pi}$ has been split into components α and β. In this case, both models react to differences in their long-run equilibrium specified by the cointegrating vector $(1, \beta)$ through α. The benefit in representing the model in this way is that α can be interpreted as the speed of adjustment parameter. Concretely, in this scenario, x_1 and x_2 will increase and decrease respectively if there was a positive deviation in the long-run equilibrium last term, and the speed of this adjustment corresponds to the size of their α.
It is also possible to allow for deterministic trends in the relationship. Consider we rewrite Equation 2 as:

$$\Delta \boldsymbol{x}_t = \boldsymbol{\mu}_0 + \boldsymbol{\mu}_1 t + \mathbf{\Pi}\boldsymbol{x}_{t-1} + \sum_{i=1}^{p} \mathbf{\Pi}_i \Delta \boldsymbol{x}_{t-i} + \boldsymbol{\varepsilon}_t \tag{6}$$

and we define $\boldsymbol{\mu}_0 \equiv \boldsymbol{\alpha}\boldsymbol{\beta}_{\mathbf{0}} + \boldsymbol{\gamma}_{\mathbf{0}}$ and $\boldsymbol{\mu}_1 \equiv \boldsymbol{\alpha}\boldsymbol{\beta}_1 + \boldsymbol{\gamma}_1$, such that we get:

$$\begin{aligned}
\Delta \boldsymbol{x}_t &= \boldsymbol{\mu}_0 + \boldsymbol{\mu}_1 t + \mathbf{\Pi}\boldsymbol{x}_{t-1} + \sum_{i=1}^{p} \mathbf{\Pi}_i \Delta \boldsymbol{x}_{t-i} + \boldsymbol{\varepsilon}_t \\
&= \boldsymbol{\alpha}\boldsymbol{\beta}_0 + \boldsymbol{\gamma}_0 + (\boldsymbol{\alpha}\boldsymbol{\beta}_1 + \boldsymbol{\gamma}_1)t + \mathbf{\Pi}\boldsymbol{x}_{t-1} + \sum_{i=1}^{p} \mathbf{\Pi}_i \Delta \boldsymbol{x}_{t-i} + \boldsymbol{\varepsilon}_t \\
&= \boldsymbol{\alpha}(\boldsymbol{\beta}, \boldsymbol{\beta}_0, \boldsymbol{\beta}_1) \begin{pmatrix} \mathbf{x}_{t-1} \\ \mathbf{1} \\ \mathbf{t} \end{pmatrix} + \boldsymbol{\gamma}_0 + \boldsymbol{\gamma}_1 t + \sum_{i=1}^{p} \mathbf{\Pi}_i \Delta \boldsymbol{x}_{t-i} + \boldsymbol{\varepsilon}_t
\end{aligned}$$

Following the methodology of both Juselius (2006) and Johansen (1995) we can determine five cases:

1. $\boldsymbol{\mu}_1 = \boldsymbol{\mu}_0 = \mathbf{0}$. No deterministic components in the data.

2. $\boldsymbol{\mu}_1 = \boldsymbol{\gamma}_0 = \mathbf{0}$ but $\boldsymbol{\beta}_0 \neq \mathbf{0}$. A constant restricted to be in cointegrating relations.

3. $\boldsymbol{\mu}_1 = \mathbf{0}$ but $\boldsymbol{\mu}_0$ is unrestricted. A constant in cointegrating relations, linear trend in levels.

4. $\boldsymbol{\gamma}_1 = \mathbf{0}$ but $(\boldsymbol{\gamma}_0, \boldsymbol{\beta_0}, \boldsymbol{\beta_1}) \neq \mathbf{0}$. A trend restricted to be in cointegrating relations, linear trend in levels.

5. No restrictions on $\boldsymbol{\mu}_0$ or $\boldsymbol{\mu}_1$. Unrestricted trend and constant. Quadratic trend in levels.

Case 1 is only applicable if all series have zero mean. Case 2 is appropriate for nontrending data with nonzero means. Case 3 is a deterministic cointegration model, in which the relations eliminate both the stochastic and deterministic trends in the data. Case 4 is a stochastic cointegration model, in which only the stochastic trend is eliminated. Finally, case 5 has quadratic trends in the levels and is only applicable if actual quadratic trends a present in the data.
Cases 1 and 5 are rarely applicable, and regular models follow either case 2, if none of the series appears to have a trend, case 3, if the trends are believed to be stochastic, or case 4, if some series appear trend stationary. In this thesis, I model VECMs with the specifications of cases 2, 3, and 4 in order to determine which best captures the carbon price market dynamics.

3.2.3 Testing for cointegration

The use of an error correction term is only valid if the variables are cointegrated. If this is not the case, we could simply estimate a VAR in differences. There are two main ways to test for cointegration: the four-step procedure proposed by Engle and Granger (1987) and the maximum likelihood estimator of Johansen (1988). In this paper I use the latter method as that of Engle and Granger is less useful in instances with multiple variables and a small dataset, and the Johansen test permits more than one cointegrating relationship.
Matrix $\mathbf{\Pi}$ in equation 2 contains in its rows the cointegrating vectors. Because of this, the rank of the matrix determines the number of cointegrating relationship present between the variables. The Johansen is therefore nothing more than a simply test to determine the rank of matrix $\mathbf{\Pi}$. Note that if the rank is zero, and all elements in $\mathbf{\Pi}$ are zero, the variables are not cointegrated. If the rank instead is n we can conclude that all variables are stationary and a VECM is not necessary. The interesting cases arise with values of rank r between zero and n.
The Johansen procedure sequentially tests the rank of $\mathbf{\Pi}$. Using the maximum eigenvalue test, the null hypothesis is $r = r_0$, with r_0 the rank currently being tested

for. The alternative hypothesis is $r = r_0 + 1$. In other words, starting with $r_0 = 0$ we test whether r_0 is the rank of $\mathbf{\Pi}$ and once we reject this hypothesis we take r_0+1 as the estimate of $\mathbf{\Pi}$'s rank.

3.2.4 Cointegration and structural breaks

The presence of structural breaks has several consequences for the modelling of VECMs. Firstly, the tests to determine presence of structural breaks are not as efficient in the presence of structural breaks. Secondly, it is hard to determine what type of break is, in reality, present. In a VECM, there could be a break in the deterministic terms, in the error correction parameters, in the short-run dynamics, or even in the cointegrating relationship itself.

Gregory and Hansen (1996) show that the presence of structural breaks limit the power of cointegration tests. Specifically, tests might fail to reject the null hypothesis of no cointegration when such a relationship is actually present. They provide a methodology to test for cointegration in situations with a structural break, using the following four models:

1. $x_{1t} = \mu + \beta x_{2t} + \varepsilon_t$
2. $x_{1t} = \mu_1 + \mu_2 \mathbb{I}[t > \tau] + \beta x_{2t} + \varepsilon_t$
3. $x_{1t} = \mu_1 + \mu_2 \mathbb{I}[t > \tau] + \alpha t + \beta x_{2t} + \varepsilon_t$
4. $x_{1t} = \mu_1 + \mu_2 \mathbb{I}[t > \tau] + \beta_1 x_{2t} + \beta_2 x_{2t} \mathbb{I}[t > \tau] + \varepsilon_t$

where $\mathbb{I}$ is an indicator function which is 1 for all dates after a break specified by τ and 0 otherwise.

Here, model 1 is simply a standard two-variable model for cointegration. Model 2 allows for a level shift in the equilibrium equation. Model 3 is similar to model 2, but includes a time trend. Model 4 allows for the slope vector β to change as well, modelling a regime shift.

All models test the null hypothesis of no cointegration by estimating the specified models with ordinary least squared and performing unit root tests on the residuals. Because a structural break might not be known beforehand, these tests can be performed for all possible break dates, selecting the break date resulting in the lowest test statistic.

Structural breaks also pose significant difficulties for the estimation of a VECM. Some structural breaks can straightforwardly be accounted for. A simple dummy variable can for example account for a break in level. Breaks in the actual cointegrating relationship themselves, and all related parameters, are much harder to account for. Methods to do so are still in its infancy, and are rarely applied in practice. I follow Pala (2013), who suggests dealing with structural breaks by modelling the sub-samples and investigating the model attributes individually. A superior method of dealing with structural breaks in VECMs has been proposed by Hansen (2003). His flexible VECM allows all variables to change over time in a piecewise manner. This model has the following form:

$$\Delta \boldsymbol{x}_t = \boldsymbol{\alpha}(t)\boldsymbol{\beta}(t)\boldsymbol{x}_{t-1} + \boldsymbol{\gamma}_0(t) + \boldsymbol{\gamma}_1(t)t + \sum_{i=1}^{p} \boldsymbol{\Pi}_i(t)\Delta \boldsymbol{x}_{t-i} + \boldsymbol{\varepsilon}_t \tag{7}$$

Hansen (2003) further introduces a generalized reduced rank regression technique to estimate these parameters. Unfortunately, this estimation technique is beyond the scope of this thesis.

3.3 Model evaluation

3.3.1 Chow test

The Chow test is a common and efficient way to determine if a structural break is present in a dataset, given a certain model. Suppose we wish to model a time series as:

$$y_t = a + bx_t + \varepsilon_t, \qquad t = 1, ..., T \tag{8}$$

and we suspect a break is present at time $t = p$. We then split the model up in two:

$$y_{1t} = a_1 + b_1 x_t + \varepsilon_t \qquad t = 1, ..., p \tag{9}$$

$$y_{2t} = a_2 + b_2 x_t + \varepsilon_t \qquad t = p + 1, ..., T \tag{10}$$

The null hypothesis is that $a_1 = a_2$ and $b_1 = b_2$ under the assumption that ε is independently and identically normally distributed.
The Chow test statistic is defined as:

$$Chow = \frac{(SSR - (SSR_1 + SSR_2))/k}{(SSR_1 + SSR_2)/(N_1 + N_2 - 2k)} \tag{11}$$

with $Chow \sim F(k, N - 2k)$, N_1 and N_2 are the number of observations in

submodel 1 and 2 respectively (so in the above example $N_1 = p, N_2 = T - p$), SSR is the sum of squared residuals for the relevant model calculated as: $SSR = \sum_{t=1}^{T}(\varepsilon_t^2)$, and k is the number of parameters (2 in the above example).
It is possible that the model shows a structural break, but that this is only caused by a level shift. This means that the regression parameters need not necessarily be different, and we could capture the level difference by introducing a dummy variable in the global equation (Equation 8):

$$y_t = a + d\mathbb{I}[t > p] + bx_t + \varepsilon_t, \qquad t = 1, ..., T \tag{12}$$

with $\mathbb{I}[A] = 1$ if A happens and 0 otherwise. In this way, variable d indicates the level shift present at time p.
I use both these methods to investigate possible structural breaks in the carbon prices. I test for breaks during two periods, the first being June 2011, after which a period of strong carbon price decline sets in and coincides with the peak of the European debt crisis and subsequent volatility on the markets. The second period I investigate is January 2013, as this is the start of Phase III on the EU ETS. Interestingly, the price dynamics before the first and second period I test appears similar, so I use the specification of Equation 12 to investigate if the intermittent period was simply a drop in level.

3.3.2 Augmented Dickey Fuller test

It is necessary to know the stationarity of all variables in order to model them correctly. If all series are stationary we can model the data in their levels, using for example ordinary least squares or the VAR model described above. If variables show presence of a unit root, it would be necessary to either model their first differences (if they are not cointegrated) or adjust the VAR model to a vector error correction model (if they are).
The Augmented Dickey-Fuller test is proposed by Dickey and Fuller (1979). It tests for the presence of a unit root, and therefore stationarity, by applying the following model:

$$\Delta x_t = \alpha + \beta t + \gamma x_{t-1} + \delta_1 \Delta x_{t-1} + ... + \delta_{p-1} \Delta x_{t-p+1} + \varepsilon_t \tag{13}$$

The test is then carried out under the null hypothesis $\gamma = 0$ against the alternative $\gamma < 0$, with the test statistic:

$$DF_\tau = \frac{\tilde{\gamma}}{SE(\tilde{\gamma})} \tag{14}$$

The test statistic has a Dickey-Fuller t-distribution with critical values provided by Dickey and Fuller (1979).
Perron (1989) argues that if the series has a structural break the ADF is biased towards not rejecting the null hypothesis. Instead, Perron (1997) proposes the following model:

$$\Delta x_t = \alpha_0 + \alpha_1 D_c + \beta_0 t + \beta_1 t D_t + \gamma x_{t-1} + \delta_1 \Delta x_{t-1} + ... + \delta_{p-1} \Delta x_{t-p+1} + \varepsilon_t \tag{15}$$

with D_c and D_t the constant and trend dummy respectively, which are 1 for $t > t_{break}$ and 0 otherwise. The model does not assume a structural break, but rather tests for all possible breaks while minimising the DF test statistic.
I use this model to ensure that conclusions on stationarity hold even if we find structural breaks using the Chow tests for the periods June 2011 and January 2013. Lumsdaine and Papell (1997) show that allowing for a second break adds even more power to the test, but their method is beyond the scope of this thesis.

3.3.3 Goldfeld-Quandt test

A time series is called homoskedastic if its variance is constant over time. In modelling, homoskedasticity is often assumed as it simplifies the underlying mathematics. If, however, the data is not actually homoskedastic, but rather heteroskedastic, estimators of certain parameters may be less efficient. Although we are not directly concerned with the modelling of the variance, this does affect the significance we attribute to the model parameters and influences the certainty we can attribute to forecasts.
In real data heteroskedasticity is often present and regularly scales with the value of the variable. For example, if a price of security is high it often fluctuates in absolute terms more than if the price is low. To investigate this specific case of heteroskedasticity I use the test proposed by Goldfeld and Quandt (1965).
The Goldfeld-Quandt test follows the following procedure:

1. Order the data by magnitude.

2. Divide the dataset in three separate sets. In other words we have a set with the third smallest observations, a set of the middle third, and a set with the third largest observations.

3. Estimate a simple regression on the smallest and largest observation sets, and calculate their sum of squared residuals.

4. Calculate the test statistic defined as :

$$GQ = \frac{SSR_2/(n_2 - k)}{SSR_1/(n_1 - k)} \tag{16}$$

where $GQ \sim F(n_2 - k, n_1 - k)$, n_i is the number of observations in set i, SSR_i is the sum of squared residuals of set i, and k is the number of parameters in the model.

Because of the characteristics of the dataset this thesis investigates, the observations are already roughly ordered by magnitude over time. I therefore divide the dataset up in three time periods. Because of this, I actually use a slight adjustment to the Goldfeld-Quandt tests and not only test for heteroskedasticity over magnitude but also over time. I keep the test statistics and evaluations as is.

4 Data

This thesis focusses on the EU ETS, and the European Allowances and Certified Emission Reductions in particular. CERs are a relatively new product, the time series for the CER spot prices starts on the twelfth of March 2009. I therefore use the daily spot settlement prices for the EUAs and CERs traded on the EU ETS from April 2009 until July 2015. The literature is divided between the use of spot prices versus futures prices, and many favour futures prices due to the EUA spot price dropping to zero between phase I and phase II. The reason for this is that it was not allowed to bank phase I credit and use them during phase II, so the allowances for phase I became worthless when the phase reached its end (see figure 20 in Appendix 7.1). For this reason research during this transition period has focussed on futures, who do not inhibit this price shock. This is no longer a necessity as the limited banking restriction has been lifted between phase II and III. The shock in question is not included in our dataset as phase I ended December 2007. Because of this, and the fact that working with futures would necessitate the stitching together of various contracts, I model the spot prices exclusively.
Four important types of predictive variables have been identified for the EUA price, and are included in this study. They are economic indicators, energy commodities, climate variables and exchange rates.
Energy commodity prices are important drivers of the carbon markets mainly because electric power generators (which take up 39% of the European CO_2 emissions

(Christiansen et al., 2005); (Delarue et al., 2008)) have the ability to switch between their fuel inputs (Bunn and Fezzi, 2007); (Convery and Redmond, 2007); (Kanen, 2006). The most important energy commodities for the carbon price are oil, coal, gas, and electricity (for which I use the ICE Crude Oil Brent continuous future, ICE Natural Gas 1-month future, ICE Coal near month future, and ICE Electricity Base Quarter continuous future respectively). Oil is often found to be important for the allowance price, although the recent price drop of oil might have changed the energy equilibrium. As the price of oil has become less of a restricting factor, other commodities such as gas could have become a relatively more important driver of the carbon price. The expected effect of oil is not entirely clear. Conventionally, rising oil prices are thought to coincide with a reduction in economic activity. Baumeister and Hamilton (2015) argue that this generally holds, although they demonstrate that only price increases due to supply shocks lead to an economic reduction in the long run, whereas price shocks due to demand shocks do not. On the other hand, Hooker (1996) shows that after 1973 the oil price appears to no longer Granger cause the U.S. economic indicators. It can thus be argued that the economy influences the oil price through simple market mechanisms. Specifically, if the economy is growing rapidly, so is the demand for oil due to its various and essential roles in economic activities. Inconveniently, these effects provide contradictory interpretations regarding the oil price. A high oil price can either forebode a future economic downturn, or be an indication of a booming economy. Coal and gas are thought to be very influential because of their role in electric power generation. A large price difference between the two would make it attractive to switch fuel for power plants, resulting in a change in their emissions and therefore carbon credit demands as coal is a more polluting way of power generation. It is possible to directly proxy the abatement opportunities using a switch variable, as is done by Alberola et al. (2008), Creti et al. (2012), and Mansanet-Bataller et al. (2011). This switching price is the main interpretation of the effect the coal and gas price have on the carbon prices. Because there can also be other effects at play I do not model this switching price directly but simply work with the prices themselves. Finally, electricity prices are also thought to be relevant to the carbon markets through their obvious relation with the electric power generation industry. The energy variables are referred to as OIL, GAS, COAL, and ELEC.

Economic indicators are interesting as they are a measure of economic activity, and a high economic activity is usually thought to coincide with higher than usual emissions. As a general European market indicator I use Euro Stoxx 50, the stock index containing the largest and most liquid 50 stocks of the Eurozone traded on Eurex.

The index started at a value of 1,000 on February 28, 1998. To bring the value of the index closer to the value of all other variable, I adjust it to a value of 100 at the start of our period (April 2009). Next, Chevallier (2011a) indicates that an EU 27 seasonally adjusted industrial production index covering total industry excluding construction is a successful economic indicator targeting industry, and therefore the demand side of the EU ETS, in particular. This index is provided by Eurostat. I use a yield spread as a variable indicating the expectation of future economic performance. The yield spread I use is the difference between the 1 year Treasury constant maturity rate and its 10 year counterpart. In general, a negative yield curve indicates that an economic downturn is expected. I also use a credit spread, the difference in the rate of bonds with the same maturity but different riskiness, as an economic indicator. A widening credit spread shows the deterioration of corporate and private creditworthiness. The spread I use is the Bank of America Merill Lynch US Corporate BBB Option-Adjusted Spread and it is, like the Treasury rates, provided by the Federal Reserve Bank of St. Louis. The economic variables are referred to as STOXX50, IND27, TERM, and CREDIT.
Also relevant for carbon price modelling are exchange rates for which I use the daily exchange rates provided by the European Central Bank (ECB). The USD/EUR exchange rate is thought to have two opposing effects on the carbon price: on the one hand through the substitution of energy sources, as the European energy market is mainly driven by USD denominated coal and EUR denominated (Russian) gas, and on the other hand through the effect on the economy through export (Yu and Mallory, 2014). The USD/EUR rate is also used to convert the oil and coal prices to Euro. The same is done for gas and electricity using the EUR/GBP rate, also provided by the ECB. The USD/EUR rate is referred to as USD.
Finally, climate indicators are sometimes found to be significant drivers of the carbon market. Temperature is the most prominent of these. The idea is that low temperatures cause a rise in energy demand, through the increased necessity for heating, leading to the need for more carbon emissions affecting carbon prices. The same applies to high temperatures leading to more cooling in summer, although this effect is probably less profound in Europe. I use daily temperature (expressed in Celsius) for the countries Spain, France, Germany, and the United Kingdom (in line with Alberola et al. (2008) and data provided by Klein-Tank (2002)). I first calculate the average 10-year temperature per day for Madrid, Paris, Berlin, and Central England, and combine these into a two variables. The first variable is the difference in temperature during a certain month and the 10-year average for that month. The locations are weighted based on country population. The second variable is

a dummy determining if two out of the four locations have a temperature that is at least one standard deviation below the 10-year average during the cold months (defined as October-March) or two out of the four location have a temperature at least one standard deviation above the 10-year average during the summer months. This accounts both for the possibility that the relationship is not a linear one, and that the differences have a different relevancy during different seasons. The weather variables are referred to as TEMP and TEMPD for the regular variable and dummy respectively.
Due to the large number of variables I divide them up in two categories to estimate two separate models: one model contains all the energy variables, while the other contains all the economy ones. I include the temperature variables in the energy model, as they are expected to be influential through changes in the demand for energy. These models are still sizeable, so initial analysis is done with an even smaller model. For this I select one variable from either model, namely the oil price and industrial production. The oil price is interesting as it is generally considered the most important energy commodity in the market. Industrial production is also expected to be of importance, as it is closely related to the demand for carbon credits. For all variables I calculate the monthly levels by taking the first level available per month. This eliminates a lot of the short term noise which is of no concern as we are interested long-term dynamics. The dataset therefore consists of 76 monthly observations. Since we are not only interested in the connection in level between the carbon prices and the explanatory variables, but also in the relationship between their movements, the aforementioned levels are used to calculate the series' differences or (log) returns. This results in difference series of 75 monthly observations.

4.1 Descriptive Statistics

The daily settlement prices for the EUAs and CERs traded on the EU ETS can be seen in figure 1. The full series for the EUAs, starting in April 2005, can be found in Appendix 7.1, Figure 20. Visually, it is immediately clear that the market has been severely hit between 2011 and 2012. More recently the EUAs appear to have stabilised and might even be returning to their pre-crisis levels, whereas the CERs appear to have lost most of their value without hope for restoration in the near future. Interestingly, the CERs seemed to follow the EUA very closely before, and during, the collapse.

The monthly log returns are shown in Figure 2. Once again we note that the returns of the CER and EUA prices seem highly correlated, although nearing the end of 2012 the CER series appears increasingly volatile and the connection with

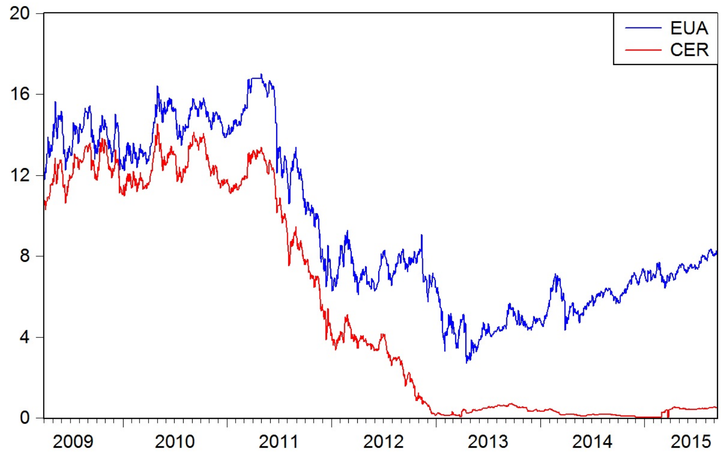


Figure 1: *Daily settlement prices EUA and CER, 01/04/2009 - 11/09/2015.*

the EUA price is a little less obvious. As we saw in Figure 1 the price of the CERs from this period onwards is very low so the volatility can at least partly be explained by small price differences leading to a large percentual return.

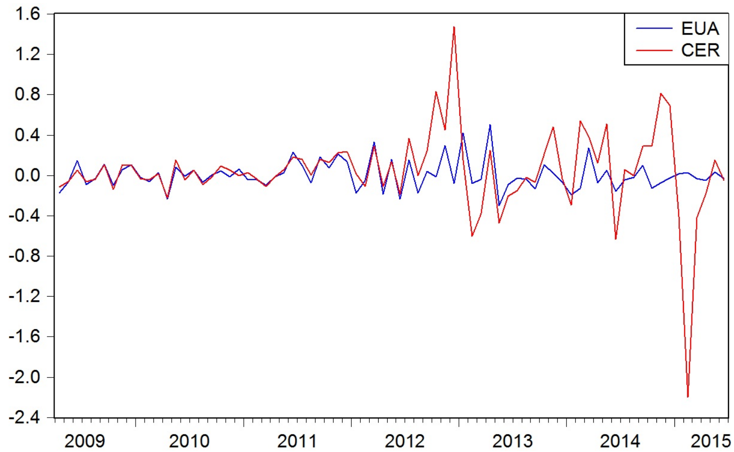


Figure 2: *Monthly log returns for EUA and CER spot prices, April 2009 - June 2015.*

The descriptive statistics for the daily settlement prices are presented in Table 1. As the graph indicated, the EUA and CER prices are strongly correlated.

Series	Mean	Median	Max	Min	Std. Dev	Skewness	Kurtosis	Covar.	Corr.
EUA	9.44	7.68	17.03	2.70	4.09	0.32	1.58	21.47	0.96
CER	5.46	3.42	14.55	0.01	5.46	0.35	1.33	21.47	0.96

Table 1: *Descriptive statistics for the daily spot prices, 01/04/2009 until 11/09/2015 (1683 obs.).*

Table 2 shows the descriptive statistics for all monthly levels. Table 3 shows the descriptive statistics of the monthly differences for all variables except the weather variables. The TEMPD dummy variable has 14 ones out of 76 observations, in other words selecting the approximately 20% most extreme months in temperature. The EUA and CER log returns are the only variables that show very strong non-normality, normality is also but to a lesser degree rejected for the credit spread.

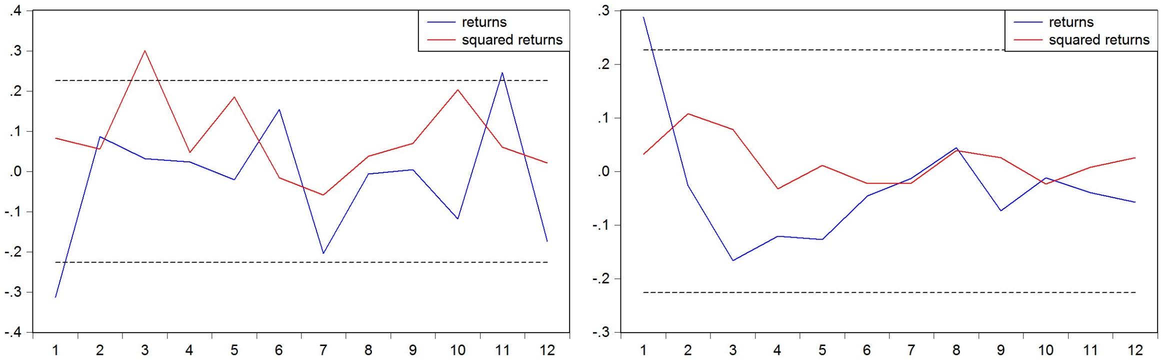
Series	Mean	Median	Max	Min	Std. Dev	Skewness	Kurtosis
OIL	71.21	77.52	94.80	36.57	14.54	-0.52	2.07
GAS	0.69	0.74	0.98	0.30	0.18	-0.48	2.13
COAL	65.65	61.15	98.44	45.12	13.30	0.54	2.23
ELEC	55.39	56.92	67.76	38.16	7.68	-0.71	2.63
STOXX50	133.78	132.71	177.11	98.62	17.43	0.30	2.82
IND27	100.55	101.37	103.94	91.28	2.97	-1.48	4.46
TERM	2.38	2.43	3.40	1.34	0.58	0.06	1.81
CREDIT	2.39	2.09	7.32	1.44	0.96	3.03	14.15
USD	1.33	1.33	1.51	1.08	0.09	-0.74	3.67
TEMP	0.12	0.04	2.82	-4.30	1.47	-0.61	3.56

Table 2: *Descriptive statistics for the monthly levels, April 2009 - July 2015 (76 obs.).*

Series	Mean	Median	Max	Min	Std. Dev	Skewness	Kurtosis
EUA	0.01	-0.02	0.50	-0.30	0.14	0.94	4.61
CER	0.04	0.01	1.47	-2.20	0.41	-1.48	14.71
OIL	-0.01	-0.01	0.20	-0.18	0.07	0.38	3.72
GAS	-0.00	-0.00	0.20	-0.26	0.10	-0.34	3.15
COAL	-0.00	0.00	0.13	-0.16	0.06	-0.34	3.01
ELEC	-0.01	-0.01	0.18	-0.16	0.07	0.16	3.15
STOXX50	-0.01	-0.01	0.12	-0.12	0.05	0.26	2.99
IND50	0.00	0.00	0.01	-0.01	0.00	0.04	3.46
USD	0.00	0.00	0.09	-0.07	0.03	0.27	3.51
TERM	-0.00	-0.00	0.08	-0.11	0.04	-0.11	3.35
CREDIT	0.02	0.03	0.20	-0.26	0.09	-0.60	4.24

Table 3: *Descriptive statistics for the monthly differences, April 2009 - June 2015 (75 obs.).*

Figure 3 shows the autocorrelations for the log returns and log squared returns for the EUA and CER series. Twelve lags are included since these are monthly returns and twelve lags account for a full-year autocorrelation analysis. The CER series show almost no autocorrelation, except for the log returns in the first lag. The EUAs also have significant autocorrelation for returns in the first lag, as well as in the eleventh. Furthermore, EUAs have significant autocorrelation at the third lag for the squared returns. These results indicate that there is merit in at least including an autocorrelation term for the first lag in a model for both time series.



(a) EUA autocorrelations

(b) CER autocorrelations

Figure 3: *Autocorrelations for logarithmic returns and squared returns of the daily EUA and CER futures prices. The dotted lines represent the critical value at the 5% significance level.*

I perform a Chow break test to analyse the presence of breaks in the time series. I perform this test at two specific points in time. The first is between the months May and June of 2011. This date is interesting as it is the start of a price collapse and has been a focus of several studies. The price collapse appears to have mainly been caused by overallocation of allowances, in combination with economic distress. The second break I test is between December 2012 and January 2013, as this is the end of phase II and the start of phase III which coincides with changes in carbon regulations, expected to have an effect on carbon prices and their dynamics. I perform the test using the simple model:

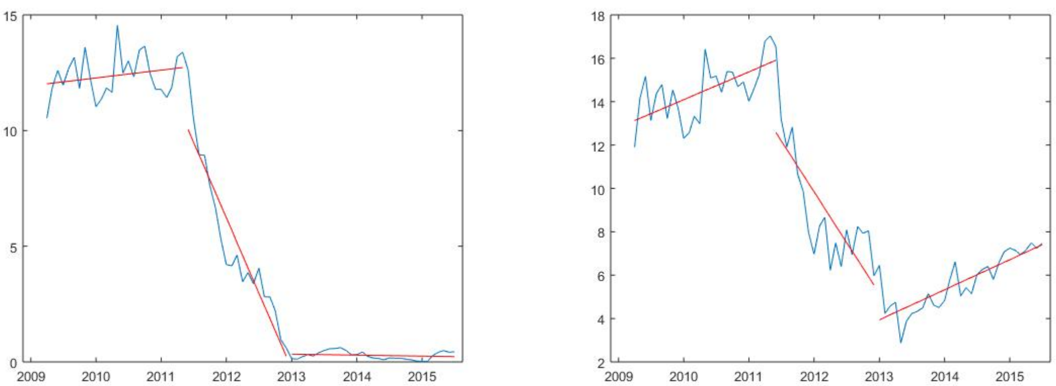
$$
\begin{aligned}
y_t &= a + bt + \varepsilon_t & t &= 1, ..., T \\
y_t &= a_1 + b_1 t + \varepsilon_t & t &= 1, ..., p \\
y_t &= a_2 + b_2 t + \varepsilon_t & t &= p + 1, ..., T
\end{aligned}
$$

where y_t is the price or log return of the CERs or EUAs at month t and p is 26 in the first test, indicating May 2011, and 46 in the second test for December 2012. The test results for the prices can be found in Table 4, relevant critical values are 4.91, 3.12, and 2.38 for the 1, 5, and 10% significance level respectively (the test statistic has an $F(2, 74)$ distribution). For all tables in this thesis, *, **, and *** indicates significance at the 1, 5, and 10% level respectively. It is immediately clear that for both breaks investigated the time series show a structural break at the 1% significance level. The regression results over the different periods are presented in Figure 4. We notice that although the constant is clearly different, the slopes of the first and third period appear to be similar. This is also demonstrated by the

regression results, as the b_1 of the first regression is close to the b_2 of the second. We can formally test this using a t-test, with the critical values 2.40, 1.67, and 1.30 for the 1, 5, and 10% significance level respectively. I find no significant difference for the EUA prices (test statistic of 0.97) and only significance at the 10% level for the CER prices (test statistic of 1.43). This indicates that in the period June 2011 - January 2013 the price series have undergone a break in level, but their time dependency has not been significantly altered. Therefore, I consider the possibility that the price dynamics in the first and third period are equal.
The Chow test is based on the assumption of stationarity of the data. To investigate the validity of the results of these Chow tests, I test whether or not this assumption is justified.

Break Tested	Test statistic	a_1	a_2	b_1	b_2
CER June 2011	52.05***	12.00	9.81	0.03	-0.15
CER January 2013	20.14***	15.67	0.58	-0.28	-0.00
EUA June 2011	41.85***	13.02	10.46	0.11	-0.07
EUA January 2013	28.83***	16.48	-2.52	-0.19	0.13

Table 4: *Chow break test statistics for monthly CER and EUA prices.*



(a) CER regression results

(b) EUA regression results

Figure 4: *Regression results for monthly EUA and CER prices.*

All variables' level and difference series are tested for presence of a unit root, using the Augmented Dickey-Fuller test with two model specifications: including only a constant and including a constant and a time trend. Results are presented in Table 5 and Table 6 for the levels and differences respectively.
Critical values for the ADF test with a constant are -2.60, -1.95, and -1.61 for the 1, 5, and 10% significance level respectively. For a model with a trend they are -4.09, -3.47, and -3.16. For the levels, we see that all variables except IND27 and CREDIT

fail to reject the null hypothesis, so must be considered integrated of the first order. IND27 only significantly rejects the null hypothesis at the 10% significance level, and only for the model without a time trend, so is also regarded as non-stationary. Due to the stationarity of CREDIT I handle it as an exogenous variable when modelling a VECM. The weather variables are also considered exogenous, as the notion that macroeconomic variables influence the temperature is meaningless. For the differences, all variables reject the presence of a unit root at the 1% significance level so we can conclude that no unit root is present and all differences are stationary.
Because the carbon prices show presence of structural breaks, this ADF test is insufficient to assume stationarity. The presence of a structural break leads to a bias in the ADF test resulting in a failure to reject the null hypothesis where this would be appropriate. Furthermore, Campos et al. (1996) argue that the apparent presence of a unit root due to structural breaks can lower the power of cointegration tests, which I wish to perform at a later stage. Therefore I also perform the Perron (1997) unit root test on the carbon prices, allowing for a structural break in both the price and level. The test statistics are -3.46 and -3.01 for the EUA and CER prices respectively, both failing to reject the null hypothesis of non-stationarity with a structural break (critical values are -5.45, -4.83, and -4.48 for the 1, 5, and 10% significance level respectively). Although this test allows only for a single structural break, I consider the carbon prices' non-stationarity sufficiently demonstrated.
The results of non-stationarity has important implications for the Chow tests performed previously. Specifically, because the Chow test assumes stationarity of the data, the significance of the test is no longer valid. The results remain interesting to this research, however. The strong prior information indicating that breaks could be present at these two dates, coupled with the crude statistical evidence from the Chow test, demonstrates that it is quite likely that there are structural breaks at these dates. This possibility has to be taken into account when modelling the entire sample.

In the Chow test, I showed that the slope for the first and third period might be similar. Perhaps this is not the case for the volatility of the prices. The CER prices especially seem to show significant heteroskedasticity, with the volatility being much higher in the first period, when the prices are high as well, than in the third where the prices are low. I test for the presence of heteroskedasticity by performing a Goldfeld-Quandt test, which is particularly easy as the prices are already divided into three sub-periods roughly ordered by their volatility. The test statistic for the EUA and CER are 4.32 and 26.57 respectively, both well above the 1% critical value of 2.55. I conclude that there appears to be presence of multiplicative heteroskedas-

Series	Constant	Trend
EUA	-0.89	-2.06
CER	-1.45	-1.67
OIL	0.04	-1.51
GAS	-0.23	-1.39
COAL	-0.16	-1.84
ELEC	0.36	-2.78
STOXX50	0.99	-1.98
IND27	1.87*	-2.79
TERM	-0.53	-1.85
CREDIT	-4.98***	-8.81***
USD	-0.70	-2.23

Table 5: *Augmented Dickey Fuller test statistics for monthly levels, April 2009 - July 2015.*

Series	Constant	Trend
EUA	-11.89***	-11.83***
CER	-6.30***	-6.28***
OIL	-6.79***	-7.18***
GAS	-8.33***	-8.48***
COAL	-8.79***	-9.09***
ELEC	-8.11***	-8.07***
STOXX50	-8.34***	-8.30***
IND50	-9.99***	-10.99***
USD	-8.84***	-8.95***

Table 6: *Augmented Dickey Fuller test statistics for monthly differences, April 2009 - June 2015.*

ticity, which could be mitigated by applying a logarithmic transformation on the prices.
The resulting log price series are presented in Figure 5. This figure indicates that the EUA price could be improved by using the log transformation, but the transformation does not seem to visually improve the CER price. This can be explained by the low prices of the CERs and the potential inaccuracy of the CER prices due to the price being specified up to 0.01 USD precision. Using the log prices would be beneficial to account for the heteroskedasticity mentioned previously, and also makes transitioning from prices to returns more natural as the log return is simply the first difference of the log prices. Another important factor, however, is whether or not the log prices show the same structural breaks as the regular prices do.
Results of the Chow break test for the log prices are shown in Table 7. Both breaks remain significant, and for the EUA prices the slope of the first period once again approaches the slope of the third, although this is rejected with a t-statistic of 5.86. The difference in slopes for the CER is also rejected with a test statistic of 1.81, although this is between the 5 and 1% critical values. This is surprising, as the difference in slope is much larger than for the log EUA prices, but can be explained by the much larger variance for the CERs in the third period. The regression results are also shown in Figure 6.
The Goldfeld-Quandt test statistics, comparing the volatility in period I and III, are 0.27 and 0.01 for the EUA and CER log series respectively, both well below the 10% critical value of 1.66. This indicates that the log transformation is successful at eliminating the heteroskedasticity present in the regular prices.
Based on these results it is hard to determine whether or not the log transformation is beneficial. On the one hand, the log transformation makes for a more natural transition between prices and returns, and we do not have to take heteroskedasticity into account. On the other hand, the transformation does nothing to solve the apparent presence of structural breaks, and makes the CER price series much more volatile and extreme. When modelling, I start with both the regular price and log price series, and based on the goodness of fit I select one for close examination.

Break Tested	Test statistic	a_1	a_2	b_1	b_2
log CER June 2011	12.30***	2.48	4.46	0.00	-0.10
log CER January 2013	14.23***	3.21	0.39	-0.05	-0.03
log EUA June 2011	18.89***	2.79	2.29	0.01	-0.01
log EUA January 2013	62.82***	2.87	0.21	-0.02	0.02

Table 7: *Chow break test statistics for monthly log CER and EUA prices.*

The Chow break test is also performed on the carbon log returns, the results

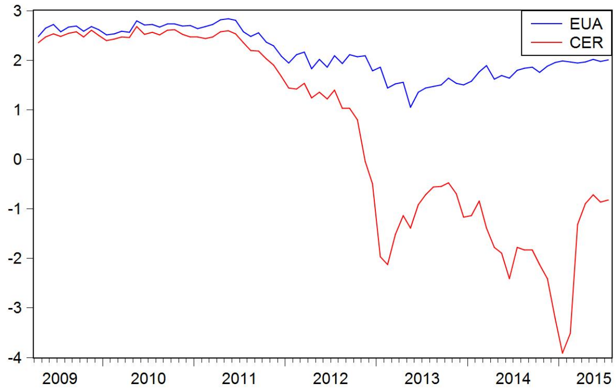
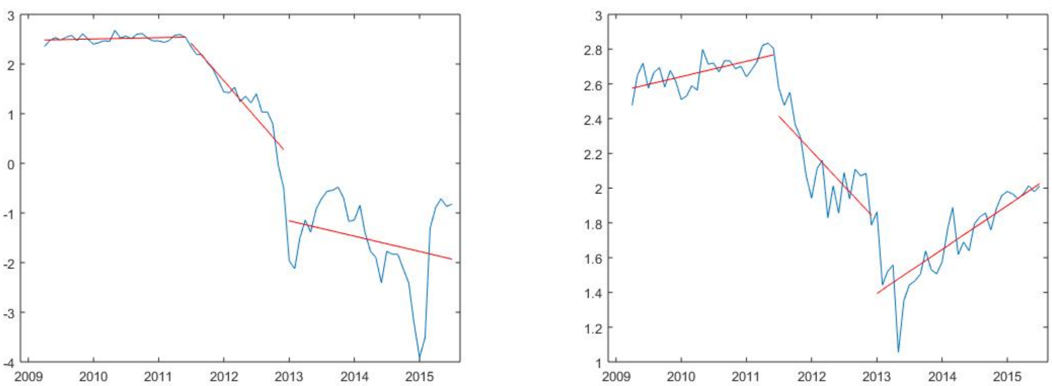


Figure 5: *EUA and CER log prices.*



(a) log CER regression results

(b) log EUA regression results

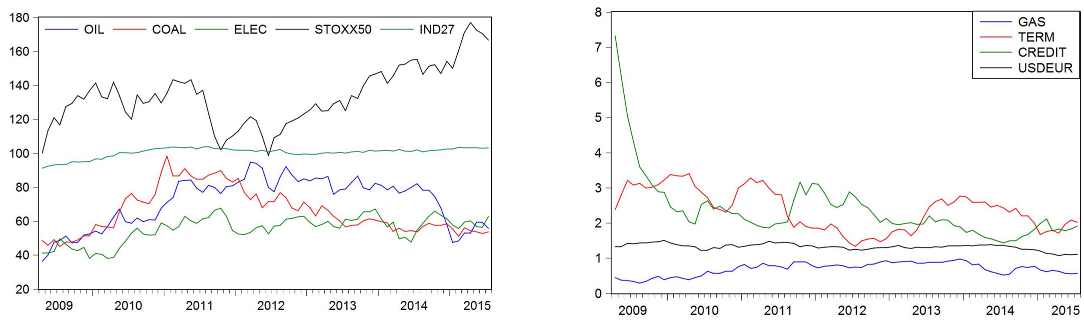
Figure 6: *Regression results for monthly log EUA and CER prices.*

of which are found in Table 8. Critical values are almost equal to those mentioned in the break test for the prices. For the returns, no structural break is found for any significance level, indicating that the EUA and CER log returns can simply be modelled over the entire period. These results are not necessarily surprising, but shed some more light on the possible breaks present. If there is a strong break in the trend, one would expect that this break is also present in the return series due to the average return being different. An instantaneous break in level does not translate to the returns in a similar manner, however, as it simply has a single return as outlier.

Break Tested	Test statistic	a_1	a_2	b_1	b_2
CER June 2011	1.43	-0.04	0.41	0.00	-0.00
CER January 2013	2.28	-0.14	0.01	0.01	-0.00
EUA June 2011	1.45	-0.04	0.13	0.00	-0.00
EUA January 2013	2.16	-0.04	0.00	0.00	0.00

Table 8: *Chow break test statistics for monthly CER and EUA returns.*

Finally, the time series of all other variables are presented in Figure 7, and given their behaviour there is no reason to suspect that any of these variables have significant breaks we should be concerned about. The only noteworthy breaks are the steep decline of the oil price in the last months of 2014 and several high outliers at the beginning of the credit series.



(a) Monthly prices and values of OIL, COAL, ELEC, STOXX50, and IND27.

(b) Monthly prices and values of CER, EUA, GAS, TERM, CREDIT, and USD.

Figure 7: *Time series of all variables' monthly values, April 2009 - July 2015.*

5 Results

This section gives a succinct overview of the results of the application of the models discussed in section 3. I model the returns of the carbon series as a VAR model.

The prices and related variables are tested for cointegration, after which they are modelled in a VECM. I find the latter method works best, most notably in a small model containing the two carbon series, the oil price, and the industrial production index.

5.1 VAR

Since the differences are all stationary, we can model them as a VAR model. Furthermore, since there is no significant break in the data for the difference series, we can consider the entire sample. I model two separate VAR models, one containing all energy related variables and one containing all those related to the economy. The energy and economy model have a temperature variable and CREDIT as exogenous variables respectively. The energy model is estimated twice, once with TEMP and once with the dummy TEMPD. I find that TEMP works best, so the results are presented here. Results for the model including TEMPD are presented in Appendix 7.2 Table 23. These models are estimated for the period April 2009 until December 2014.

Table 9 shows the AIC, BIC, and log-likelihood for the energy and economy models. Both models favour only one lag for both information criteria. This suggest that the benefits of adding lags for months 2 and 3 is smaller than the costs of estimating all concerned coefficients. This could be an indication that new information being introduced in the system through a certain variable is very rapidly integrated in the levels of the other variables.

	lags	AIC	BIC	Log-L
Energy	1	-10.40	-8.84	342.94
	2	-10.06	-6.99	360.57
	3	-9.88	-5.46	386.80
Economy	1	-21.24	-20.24	620.58
	2	-19.95	-19.95	632.63
	3	-19.64	-15.22	650.38

Table 9: *Information criteria for VAR models with different lags, estimation period April 2009 - December 2014.*

The estimated parameters for the CER and EUA regressions of these two models are presented in Table 10. As this is a VAR model, similar regression results are estimated for all other variables. We are mainly concerned in the drivers of the carbon prices, and therefore only these results are shown.

The results indicate that neither an energy model nor an economy model is par-

ticularly useful for the modelling of the difference series. Specifically, no estimated parameters are significant at the 10% level, except for the CER and EUA lags themselves. Both carbon prices appear to be significantly dependent on one another. This is a little surprising as the EUAs are more liquid and are the actual main carbon-offset allowances to be used in the EU ETS, whereas the value of CERs mainly comes from the possible substitution of EUAs. Because of this, the EUAs should be expected to incorporate new information quicker than CERs, leading to a situation where CERs would follow EUAs, but not necessarily the other way around.
There are a couple of possible explanations for the lack of significance of the explanatory variables. First, it is possible that energy or economy variables are simply not strongly correlated with the carbon price, although this is unlikely due to their theoretic connection and the results of previous research. Second, the VAR model could be insufficient for the modelling of these connections. This is more likely the case, and can have several causes itself. The VAR model has been estimated using the differences of the series, but it could be better to model the levels of these variables if they have a connection in level. This would necessitate the modelling of a VECM, as we would need to incorporate error correction terms to account for non-stationarity and cointegration. This would also unfortunately necessitate us to cope with the presence of structural breaks. Alternatively, it could be the case that linear models are plainly to simple and crude for the modelling of these connections.

5.2 Cointegration

To test whether or not the non-stationary variables are cointegrated, I perform the Johansen cointegration test. Results are presented in Table 11 for the Johansen cointegration test with three lags and a trend in the cointegration equation. The value where $r = 2$ is the first estimate of the number of cointegration vectors that fails to reject the null hypothesis that the number of cointegration vectors is smaller than the number of variables, and I conclude that the variables are cointegrated. The cointegration vectors are accounted for by adding error correction terms to the VAR model.

I estimate two VECMs. One model to analyse the behaviour among the energy related variables, and one model to analyse the behaviour between the carbon prices and the economy. Temperature variables are included to the former as the climate is thought to have an effect through the demand for energy, so it theoretically fits well with the energy prices. For these two separate models I also determine the cointegration, results are presented presented in Table 12. There is one cointegrating relationship for the energy model, whereas for the economy model there are two.

	Energy		Economy	
variable	EUA	CER	CER	EUA
Constant	0.04	-0.00	0.00	0.05
	(0.05)	(0.02)	(0.02)	(0.04)
EUA_{-1}	-0.35***	-0.48*	-0.39***	-0.53*
	(0.13)	(0.27)	(0.12)	(0.27)
CER_{-1}	0.13**	0.30**	0.13**	0.37***
	(0.06)	(0.13)	(0.06)	(0.14)
OIL_{-1}	-0.20	0.89		
	(0.29)	(0.62)		
$COAL_{-1}$	0.47	-0.49		
	(0.32)	(0.68)		
GAS_{-1}	-0.38*	-0.03		
	(0.21)	(0.45)		
$ELEC_{-1}$	0.05	-0.48		
	(0.32)	(0.69)		
$TEMP_{-1}$	-0.00	0.05**		
	(0.01)	(0.03)		
$STOXX50_{-1}$			0.30	0.07
			(0.15)	(0.07)
$IND27_{-1}$			0.15	9.00
			(6.07)	(13.26)
$TERM_{-1}$			-0.31	-1.84
			(0.60)	(1.31)
USD_{-1}			-0.79	-0.40
			(0.75)	(1.65)
$CREDIT_{-1}$			0.03	0.35
			(0.24)	(0.53)
Statistics				
R^2	0.22	0.22	0.18	0.15
Log-likelihood	401.76		770.21	
AIC	-10.40		-21.24	
BIC	-19.67		14.22	

Table 10: *Parameter estimation results for the VAR Energy and Economy models, estimation period April 2009 - December 2014.*

r	test statistic	critical value 1 %	eigenvalues
0	340.87***	300.28	0.67
1	257.99***	253.20	0.60
2	189.72	210.02	0.44
3	146.37	171.09	0.40
4	108.417	135.98	0.34
5	77.38	104.96	0.32
6	48.33	77.82	0.22
7	29.54	54.69	0.18
8	14.32	35.47	0.11
9	6.00	19.94	0.08
10	0.02	6.65	0.00

Table 11: *Johansen cointegration results.*

	r	test statistic	critical value 5 %	eigenvalues
Energy	0	128.61***	117.71	0.47
	1	82.37	97.60	0.31
	2	53.74	71.60	0.26
	3	32.03	49.36	0.18
	4	17.52	31.15	0.13
	5	6.46	16.55	0.11
Economy	0	159.032***	127.709	0.531
	1	104.45**	97.60	0.44
	2	62.28*	71.480	0.30
	3	36.23	49.36	0.23
	4	17.41	31.15	0.150
	5	5.88	16.55	0.08

Table 12: *Johansen cointegration results for separate models.*

The previously identified presence of structural breaks could affect the cointegration relationship. I therefore also perform cointegration tests proposed by Gregory and Hansen (1996) that allow for three different types of structural breaks: a level shift (model 2), a level shift with trend (model 3), and a regime shift (model 4). They show that not accounting for structural breaks lowers the power of cointegration tests, which can result in not finding a cointegrating relationship where one is actually present. Because cointegration is already found without accounting for structural breaks, the additional tests are expected to do the same and are merely included for completion. Test statics for the three additional models are presented in Table 13, critical values as provided by Gregory and Hansen (1996) are -6.05, -6.56, and -5.31 for the 1, 5, and 10% significance level respectively. As expected, the null-hypothesis of no cointegration is significantly rejected for all alternate models. The selected breaks are quite interesting, however. The breaks for these tests are not given a priori. Instead, the tests select the break period with the lowest test statistic. The breaks indicated in these results are all very close to the breaks I tested for previously, further strengthening the case that there are meaningful structural breaks both during 2011 and during the shift between phase II and phase III.

	model	ADF test statistic	Break
Energy	2	-6.01**	2011m07
	3	-6.18***	2013m02
	4	-6.83***	2013m03
Economy	2	-5.79**	2011m08
	3	-5.76**	2011m10
	4	-6.35***	2011m07

Table 13: *ADF test statistics for cointegration tests allowing for different types of structural breaks.*

Before I estimate these energy and economy models I analyse a smaller model only including the oil price and industrial production as additional variables. A Johansen cointegration test with three lags and a trend in the cointegration equation determines that EUA, CER, OIL, and IND27 have one cointegration equation at the 5% significance level (test statistic 67.60, critical value 63.88). I therefore model these variables with one cointegration relationship.
The presence of cointegration between the variables also has important consequences for the results of the VAR model. In a way, if the variables are actually cointegrated, the VAR model can be considered misspecified as it does not account for the error correction terms actually describing the price dynamics. Therefore, it is almost certain that the following VECM models will outperform the VAR model. The

main reason for including the VAR model in this study is that is has received a lot of attention in carbon price research. These cointegration results show that this is unjustified, and that VECMs are probably more suited for the task of modelling carbon prices. The VAR results further provide an interesting benchmark, showing the difference in performance between a VAR and a VECM. Also, the VAR has been modelled using the carbon returns instead of their differences, such that it is not merely a VECM without an error correction term.

5.3 VECM

Since the EUA and CER prices are non-stationary and are cointegrated with the other variables, the VAR model is transformed to a VECM by including error correction terms.

This section has been divided in three parts. In the first part, I estimate a simple model only including EUA, CER, OIL, and IND27. The oil and industry variables are already identified by the literature as important determinants of the carbon price, and are both expected to be important drivers in their respective models. I estimate this model over three sub-periods divided by the potential structural breaks of June 2011 and January 2013. Using this smaller model first has several benefits. Firstly, I can easily estimate this model once for the regular prices and once for the log prices in order to determine which of the series can be better captured by the VECM. Secondly, the low number of variables makes it possible to estimate the model with a varying number of lags, as our dataset is small and the number of estimated parameters quickly increases with the number of variables. Finally, these smaller models can be used to determine how best to cope with the two structural breaks suspected around June 2011 and January 2013. The results of this first part merely serve to shed some light on the VECM, and are to be seen as auxiliary. The main results of this thesis are discussed in the second and third part of this section. The second part of this section builds on the model with only EUA, CER, OIL, and IND27, but tries to find the best way to model a VECM over the entire sample. In the final part of this section I focus on the estimation of two distinct models, similar to the VAR modelling. The first serves to analyse the relationship of levels in the energy market, also including the temperature variables, and the second serves to analyse the relationship between the levels in the economy.

5.3.1 Oil and Industrial Production, sub-period models

I divide the period April 2009 until December 2014 up into three distinct periods, disconnected by the suspected structural breaks. This gives us a preliminary feel of the cointegrating effects going on throughout the period, without having to worry about the possible interference of structural breaks. This methodology is a manner of dealing with structural breaks in a VECM environment, in line with Pala (2013). The results of this first part are therefore to be considered auxiliary.

Results of the VECM for the carbon prices for the three distinct periods are presented in Tables 14, 15, and 16. The models are estimated with one and two lags. Modelling more lags is infeasible given the small subsets of the data. The same models are also estimated with these series after a logarithmic conversion, these results are presented in Appendix 7.3 Tables 24, 25, and 26. For all these models I specified the VECM with a deterministic trend, or case 4 discussed in Section 3.2. The rationale for this is that the EUA and CER series appear to have different deterministic trends, and adding even more variables reduces the plausibility that the cointegrating relationship will eliminate the deterministic trends present.

All these models are estimated by normalising the cointegrating vector around the carbon allowances. Since this thesis focusses on carbon credits, it is logical to pick either the EUA or CER to do this. I opted for the EUA because the low CER prices in the third period could cause distortions, even though theoretically it should not make a difference. To investigate whether it actually makes a difference I also estimated the models normalising around the CER prices, and the results are very consistent to the results I find for normalising around EUA. Results for these alternative models are presented in Appendix 7.3, Tables 27, 28, and 29.

April 2009 - May 2011

For the first period we notice that in the model with one lag CER and OIL are significant in the cointegrating relationship. OIL is the only variable with a significant error correction parameter. This is a surprising results, as we would sooner expect the carbon prices to restore a found equilibrium than the much more economically important oil price. According to this model, if the CER price is above its suggested equilibrium price, there will be a negative equilibrium term and the oil price will decrease. This direction would make economic sense if the causality would have been the other way, as a low oil price could stimulate extra carbon emissions. Furthermore, almost none of the VAR terms are significant. The constant term, indicating a trend in levels, is not significant for the carbon prices.

The model slightly changes if we add another lag. The cointegrating relationship is now significant for at least the 10% significance level for all variables and the trend term. Apart from these changes in significance, the cointegrating vector is very similar with all signs the same as in the model with one lag. Now, however, only the EUA has a significant error correction term. This suggests that the cointegrating relationship concerns all variables, but only the carbon allowances are correcting to account for errors. According to this model if either the CER, oil price, or the industrial production are relatively high the EUA price will adjust to correct for this. Although the CER has no significant error correction term, the direction is the same as for the EUA. For industrial production this direction is intuitively clear, as high production means high demand for carbon credits. For CER prices this is also understandable, as the EUA and CER prices should not grow too far apart. Interpreting the oil price is more difficult. The oil price can have two different interpretations, as I argue in Section 4. On the one hand, a high oil price could decrease demand for carbon credits and thus lower their prices. On the other hand, a high oil price could be an indicator of economic growth, coinciding with an increase in the demand for carbon credits and thus their price. According to this model, the latter could be the case. In this model a relatively high oil price leads to an increase of the price of carbon allowances. Although only the EUA error correction term is significant in this two lagged model, both carbon error correction terms changed signs compared to the model with only one lag. Because the terms were only small in the model with one lag, this is not too disturbing. Overall, the model seems quite robust considering the small sample size. The VAR terms in the first lag show no significance, but we do find some significance for the second lag terms for the EUA price and IND27 level. Although we do find significance, the VAR terms of the second lag do not appear to capture important level movements, as they often contrast the autoregressive movement of the first lag. This is most obvious in the autoregressive terms for the carbon allowances. In the first lag, we find a highly significant positive term for the lagged EUA itself. The parameters is even larger than one, indicating explosive price movements. The effect is almost completely countered by the significant and very large negative term in the second lag. Apart from this extreme example, several other terms show instability between lags, suggesting that we might be overfitting the data. Because of this, it is not entirely clear whether the model with one or two lags should be considered more successful. The cointegrating vector in the model with two lags is significant for all variables, and it has a more logical economic interpretation. If we compare the R^2 values, we notice large increases for the EUA, CER, and IND27 levels. The increase for the EUA is explained both by the significant error correction term and the autoregressive VAR terms, although due to the opposing signs of the VAR terms the high R^2 should not be taken at face value. The reason for the large increase for R^2 is less obvious for the CER and IND27 levels, but is likely also caused by more significant VAR terms. OIL sees a stark reduction in R^2 which is explained by the fact that in the model with two lags it no longer has a significant error correction term. Finally, the log-likelihood increases moving from the model with one lag to the model with two, and the AIC decreases. The BIC, however, increases, indicating that the estimation uncertainty introduced by estimating the second lag might not be worth the log-likelihood increase.

Finally, comparing these models to their logarithmic counterpart, we notice that the results are roughly the same. However, the oil price is now also highly significant in the one lag cointegrating vector. In this model, a relatively high oil price will cause the oil price to decrease, in a sense a long-term autocorrelation. The model with two lags is also similar, although IND27 is no longer significant. The IND27 term is also very large, which is caused by the relatively high and stable value of the variable. In this model CER also has a significant error correction, and in the same direction as the EUA. This is not too surprising as one would expect the EUA and CER prices to react similarly to a disequilibrium. Another important difference between the two models is that the logarithmic model does not show the same instability in the VAR term lags as the regular model does. Overall, though, it is hard to determine if the logarithmic model outperforms the regular one. The R^2 for the logarithmic models slightly underperforms compared to the regular model for one lag, but slightly outperforms this model in the two lagged specification. The performance of the logarithmic model with two lags compared to the logarithmic model with one lag is similar in that the AIC favours the two lagged model, and the BIC favours the model with one lag.

June 2011 - December 2012

For the second period, the one lagged model has significance for the EUA, CER, and oil prices, both in the error correction terms and in the cointegrating relationship. Once again, CER and OIL have negative parameters in the cointegrating vectors, and EUA and CER have negative error correction terms whereas OIL has a positive one. Again, the coinciding of the signs from the cointegrating vector term for the oil price and the error correction terms for EUA and CER suggests that a high oil price causes high carbon prices. This again suggests that OIL functions as an indicator for a strong economy. We notice that the VAR terms are again not very significant, although slightly more relevant than in the one lagged model for the first period. In

this model the trend term is also significant in the cointegrating vector at the 10% significance level. The constant is negative and significant for both carbon prices, accounting for the strong negative trend these prices experience in this period.
The two lagged specification again finds more significance for the cointegrating vector, but much less significance for the error correction terms, where only CER has a term significant at the 10% significance level. Again, OIL and CER have the same signs in the cointegrating vector and error correction terms respectively, meaning that they move in unison. The two lagged model this period has even less significance in the VAR terms. As in the first period, the R^2 for the two lagged model is higher for EUA, IND27, and for CER in particular, while is lower, but less drastically than in the first period, for OIL. Again, the decrease of OILs R^2 could be explained by the loss of a significant error correction term, but the increase in the other three variables is left unexplained as all three lost significant terms moving from the one lagged to the two lagged model. Again, the AIC favours the model with two lags, whereas the BIC favours the model with one.
The logarithmic estimation of this model shows similar results, although now IND27 is highly significant in the cointegrating vector and EUA lost its significant error correction term. The negative sign for IND27 in the cointegrating vector and the negative error correction term with CER is again theoretically expected, as high industrial production should cause a rising carbon price, and the coinciding of the CER and OIL signs is by now unsurprising. For the two lagged model only OIL has a significant error correction term, which is negative. This is consistent with the model with one lag, because all variables in the cointegrating vector have changed sign. Still, the relationship between oil and industrial production is puzzling, as this model suggests that oil will react to a relatively high industrial production by decreasing in price, while we expect the opposite relationship to hold. Although the R^2 increases or remains the same for all variables moving from one to two lags, both information criteria now indicate the one lagged model is best. Finally, the one lagged logarithmic model outperforms its regular counterpart based on R^2 for all variables except oil.

January 2013 - December 2014

The results for the third period are for the most part consistent with those of the previous two. For one lag, we find that CER and OIL are significant in the cointegrating vector, as well as the trend term. The error correction term is only significant for CER, and again the sign of the CER error correction term and the OIL cointegrating vector term are the same. There are also several significant parameters in the VAR specification.

In the model with two lags, CER loses significance in the cointegrating vector but EUA gains a significant error correction term. Furthermore, we find several significant VAR terms. It seems like VAR effects are more important in this third period than in the previous two. Comparing the R^2 of both models we notice that apart from a small decrease for CER the other three variables seem greatly improved. The information criteria paint a different picture, however, as the AIC barely favours the model with two lags and the BIC clearly favours the one lagged model.

For the logarithmic model, the model with one lag almost entirely coincides with its regular counterpart. Again Trend, CER, and OIL are significant in the cointegrating vector and only CER has a significant error correction term. All signs are equal also. The two lagged model is slightly different, as this time OIL remains highly significant in the two lagged specification, and the EUA loses the significance of the error correction term. Even the values of the R^2 are similar, most profoundly for the models with only one lag. The model with two lags has a much lower R^2 for the carbon allowances, but improves on the emission reductions.

Preliminary conclusions

The value of the cointegrating relationships for the one and two lagged models are presented in Figures 8a and 8b for the levels and logarithmic levels respectively. For the regular levels, there are three things we notice. First, the relationship looks remarkably stable over the entire period, indicating that the VECM is a successful way of modelling the level movements of these variables. Secondly, we notice that the relationships for one and two lags are fairly similar, but the cointegrating relationship for the model with one lag is more volatile in the first period. Thirdly, we notice that the variance of the relationship value decreases when progressing through the periods. A possible explanation for this could be the heteroskedasticity in the carbon prices, as in general their price has decreased over time and their volatility likewise. If heteroskedasticity is the cause, this declining volatility should not be present in the logarithmic cointegrating relationship. The graph for the logarithmic cointegrating relationship does show a little more stability, as all movements are roughly within the same range. For the logarithmic models the relationship seems most volatile in the second period.

From these results I reach several conclusions. Firstly, the results so far appear quite promising. Even though VECMs are meant to look for long-run equilibria, the modelling of these short periods already yields some interesting results. This is

underlined by the visually rather stable cointegrating relationships.
Secondly, we find some consistency throughout the three periods. Emission reduction and oil prices are often significant in the cointegrating vector, while industrial production has less strength, at least for the models with one lag. Furthermore, the oil price seems to have a consistent effect on the carbon prices wherein a high oil price leads to an increase of the carbon prices. This could be explained by interpreting the oil price as an economic indicator.
Thirdly, the carbon prices are the variables that most often have a significant error correction term. This makes intuitive sense as this means that they adjust to errors in the equilibrium which is expected due to their relatively small importance in the economy.
Fourthly, the trend term in the cointegrating relationship is often significant, suggesting that this is a correct specification of the model. This term should not be taken as a trend in levels, however. The constant fulfils that role, and as expected we find a strong negative constant for both carbon prices in the second period. The trend term in the cointegrating relationship is difficult to interpret and is further scrutinized at a later stage.
Fifthly, the use of logarithmic levels does not significantly change the results. The R^2 of most variables is slightly higher for most variables, and in some models the cointegrating vector finds more significance for the variables when using logarithmic levels compared to regular levels. The error correction term for the EUA sometimes looses significance when switching to logarithmic prices, however, and as this is a focus point of this research I favour the use of regular levels.
Sixthly, the VAR parameters do not show a lot of significance, indicating that the error correction part of this model is the most important aspect to model the dynamics between these variables.
Finally, the use of a second lag greatly increases the found R^2 but the BIC consistently favours the use of a smaller model. Because the VAR terms do not appear to be very important, I am inclined to favour the smaller model, but I continue estimating models with two lags to investigate this matter in more detail. Not only the performance between the one lagged and two lagged models are relevant, but also their specifications. Some differences are present, but considering the small sample size the models appear rather robust already.

Cointegrating Equation

	1 lag	2 lags
Constant	162.62	87.20
Trend	1.36 (1.11)	0.70*** (0.26)
EUA_{-1}	1	1
CER_{-1}	-5.81*** (1.42)	-1.52*** (0.39)
OIL_{-1}	-0.73*** (0.22)	-0.37*** (0.06)
$IND27_{-1}$	-0.81 (1.81)	-0.71* (0.43)

Error Correction

	1 lag				2 lags			
variable	D(EUA)	D(CER)	D(OIL)	D(IND27)	D(EUA)	D(CER)	D(OIL)	D(IND27)
Constant	0.25	0.18	1.84**	0.64***	-0.17	-0.19	0.94	0.40
	(0.34)	(0.30)	(0.84)	(0.19)	(0.36)	(0.44)	(1.72)	(0.28)
EC	0.07	0.07	0.64***	0.04	-0.50***	-0.24	0.67	0.12
	(0.06)	(0.05)	(0.16)	(0.04)	(0.16)	(0.20)	(0.78)	(0.13)
$D(EUA_{-1})$	-0.42	-0.13	0.48	0.07	1.06***	-0.51	0.32	-0.13
	(0.44)	(0.38)	(1.08)	(0.24)	(0.38)	(0.45)	(1.78)	(0.29)
$D(CER_{-1})$	0.37	-0.01	0.70	0.14	0.23	-0.13	-1.32	0.25
	(0.53)	(0.46)	(1.31)	(0.30)	(0.41)	(0.49)	(1.94)	(0.32)
$D(OIL_{-1})$	0.06	0.07	0.04	-0.01	0.03	0.06	0.15	0.03
	(0.07)	(0.06)	(0.17)	(0.04)	(0.06)	(0.07)	(0.29)	(0.05)
$D(IND27_{-1})$	-0.42	-0.46	-0.46	-0.36*	-0.12	-0.27	-0.19	-0.26
	(0.40)	(0.35)	(0.99)	(0.22)	(0.31)	(0.37)	(1.47)	(0.24)
$D(EUA_{-2})$					-0.86**	-0.38	0.05	-0.54**
					(0.35)	(0.42)	(1.66)	(0.27)
$D(CER_{-2})$					0.45	-0.16	-0.88	0.55*
					(0.40)	(0.48)	(1.88)	(0.31)
$D(OIL_{-2})$					0.01	0.00	0.13	0.03
					(0.06)	(0.07)	(0.29)	(0.05)
$D(IND27_{-2})$					0.82**	0.65*	0.50	0.22
					(0.34)	(0.40)	(1.59)	(0.26)
Statistics								
R^2	0.24	0.34	0.53	0.17	0.70	0.51	0.26	0.39
Log-likelihood	-123.15				-96.60			
AIC	12.68				12.31			
BIC	14.10				14.54			

Table 14: *VECM estimation results for levels, estimation period April 2009 until May 2011.*

Cointegrating Equation

	1 lag	2 lags
Constant	67.29	-83.61
Trend	-0.21*	-0.38***
	(0.12)	(0.04)
EUA_{-1}	1	1
CER_{-1}	-1.23***	-1.65***
	(0.15)	(0.09)
OIL_{-1}	-0.30***	0.16***
	(0.05)	(0.04)
$IND27_{-1}$	-0.37	0.81**
	(0.46)	(0.37)

Error Correction

	1 lag				2 lags			
variable	D(EUA)	D(CER)	D(OIL)	D(IND27)	D(EUA)	D(CER)	D(OIL)	D(IND27)
Constant	-1.26**	-1.11***	1.59	-0.15	-0.50	-0.54*	-2.16	-0.24
	(0.64)	(0.33)	(1.84)	(0.28)	(0.68)	(0.31)	(2.02)	(0.27)
EC	-0.56*	-0.35**	2.58***	0.11	-0.09	0.56*	-2.21	0.16
	(0.32)	(0.17)	(0.92)	(0.14)	(0.76)	(0.34)	(2.26)	(0.30)
$D(EUA_{-1})$	0.54	0.57	-2.46	-0.24	0.33	-0.01	2.11	-0.48
	(0.72)	(0.37)	(2.06)	(0.31)	(0.96)	(0.43)	(2.84)	(0.38)
$D(CER_{-1})$	-1.48	-1.10*	3.52	0.37	-0.80	-0.15	-4.10	0.60
	(1.30)	(0.68)	(3.74)	(0.57)	(1.50)	(0.68)	(4.45)	(0.59)
$D(OIL_{-1})$	-0.09	-0.06	0.58**	-0.07*	-0.09	-0.12*	0.53	-0.06
	(0.09)	(0.05)	(0.26)	(0.04)	(0.14)	(0.06)	(0.41)	(0.05)
$D(IND27_{-1})$	0.13	0.04	1.83	-0.26	1.34	0.30	1.29	-0.91*
	(0.47)	(0.25)	(1.36)	(0.21)	(1.17)	(0.53)	(3.49)	(0.46)
$D(EUA_{-2})$					0.19	0.02	2.74	0.27
					(0.81)	(0.37)	(2.41)	(0.32)
$D(CER_{-2})$					-0.11	0.08	-3.51	0.28
					(1.37)	(0.62)	(4.08)	(0.54)
$D(OIL_{-2})$					0.19	0.00	-0.23	-0.10
					(0.18)	(0.08)	(0.53)	(0.07)
$D(IND27_{-2})$					0.84	0.61*	-0.76	-0.25
					(0.71)	(0.32)	(2.11)	(0.28)
Statistics								
R^2	0.25	0.25	0.50	0.51	0.27	0.46	0.48	0.62
Log-likelihood	-92.73				-68.82			
AIC	12.81				11.98			
BIC	14.25				14.22			

Table 15: *VECM estimation results for levels, estimation period June 2011 until December 2012.*

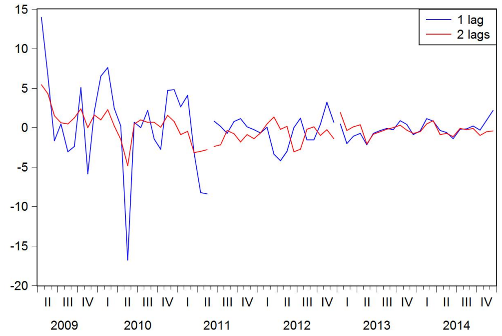
Cointegrating Equation

	1 lag	2 lags
Constant	-33.81	-17.04
Trend	-0.08** (0.03)	-0.11** (0.05)
EUA_{-1}	1	1
CER_{-1}	3.33*** (0.60)	1.28* (0.85)
OIL_{-1}	-0.08** (0.04)	0.03 (0.06)
$IND27_{-1}$	0.38 (0.26)	0.15 (0.32)

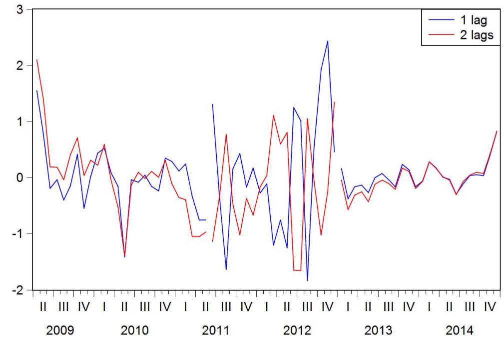
Error Correction

	1 lag				2 lags			
variable	D(EUA)	D(CER)	D(OIL)	D(IND27)	D(EUA)	D(CER)	D(OIL)	D(IND27)
Constant	0.11	-0.03**	-1.31	0.18	-0.21	-0.02	-0.34	0.35**
	(0.18)	(0.01)	(1.05)	(0.12)	(0.16)	(0.02)	(1.33)	(0.13)
EC	0.03	-0.14***	0.92	-0.02	-1.04***	-0.06*	0.26	0.19
	(0.24)	(0.02)	(1.35)	(0.16)	(0.25)	(0.03)	(2.05)	(0.20)
$D(EUA_{-1})$	-0.42*	0.07***	-0.16	-0.06	0.46*	-0.04	-1.75	-0.22
	(0.25)	(0.02)	(1.41)	(0.16)	(0.26)	(0.03)	(2.15)	(0.21)
$D(CER_{-1})$	2.95*	-0.08	-3.90	0.28	-1.08	0.04	-2.13	0.31
	(1.54)	(0.12)	(8.82)	(1.02)	(1.27)	(0.16)	(10.35)	(1.03)
$D(OIL_{-1})$	-0.02	-0.01*	0.27	-0.03	-0.02	0.01**	0.11	-0.02
	(0.05)	(0.00)	(0.27)	(0.03)	(0.04)	(0.00)	(0.29)	(0.03)
$D(IND27_{-1})$	0.05	0.02	0.29	-0.63***	0.37	-0.06*	-2.20	-1.01***
	(0.31)	(0.02)	(1.75)	(0.20)	(0.29)	(0.04)	(2.41)	(0.24)
$D(EUA_{-2})$					0.26	-0.07***	-1.47	-0.05
					(0.18)	(0.02)	(1.44)	(0.14)
$D(CER_{-2})$					-0.02***	0.26**	5.63	1.02
					(0.95)	(0.12)	(7.80)	(0.78)
$D(OIL_{-2})$					0.06	0.01***	0.00	-0.01
					(0.04)	(0.00)	(0.31)	(0.03)
$D(IND27_{-2})$					0.20	-0.07*	-3.17	-0.59***
					(0.28)	(0.04)	(2.32)	(0.23)
Statistics								
R^2	0.31	0.83	0.05	0.45	0.71	0.80	0.18	0.64
Log-likelihood	-68.69				-52.46			
AIC	8.14				8.12			
BIC	9.56				10.33			

Table 16: *VECM estimation results for levels, estimation period January 2013 until December 2014.*



(a) *Equilibrium deviations for regular levels.*



(b) *Equilibrium deviations for logarithmic levels.*

Figure 8: Equilibrium deviations for VECM with one and two lags and all three sub-periods.

5.3.2 Oil and Industrial Production, complete period models

Next, I estimate the VECM with OIL and IND27 over the entire period April 2009 until December 2014, again with either one or two lags. For this period it would be feasible to estimate additional lags, but results so far have indicated that the second lag is only a slight improvement at best, so additional lags are unnecessary. From now on I only model the regular levels as the logarithmic transformation is not clearly beneficial and found less significant results for the carbon allowances, the main subject of this study. Results are presented in Table 17.

For one lag, the results are promising. The cointegrating vector has significant parameters for all variables but the CER, and all variables have significant error correction terms implying that all variables actively react to errors in the equilibrium. Interestingly, the OIL cointegrating sign is not equal to the carbon price error correction signs. This contrasts with the results found previously. The signs of the carbon error correction terms and IND27 are the same, indicating that higher industrial production leads to higher carbon prices. This is similar to expectation and previous results. The sign of the trend term is also positive. Again, the VAR terms show low significance and do not seem to contribute much to the model. Despite the significance of the error correction specification, the R^2 for both carbon prices is a lot lower than the values of R^2 found for the sub-periods. The main reason for this is that the sub-periods are much shorter and R^2 values are naturally higher in models that have a shorter horizon. Another reason for this is that the model does not account for the structural breaks, and the constant term indicating a trend in

levels is insignificant for both the EUA and CER.
The model with two lags does not offer tangible improvements. The cointegrating vector is more or less similar, but the carbon prices no longer have a significant error correction term. VAR terms also do not show any improvement. Although the R^2 improves somewhat moving to the two lagged specification, both information criteria favour the model with one lag. Based on these results, I conclude that one lag is sufficient for modelling carbon prices with a VECM, and in the future I no longer estimate models with two lags.
The cointegrating relationship for the model with one lag is graphed in Figure 9, and again demonstrates stability and stationarity. However, there does appear to be some structural break between the first and second period. The cointegrating relationship during the first period is stable around a value of approximately minus five, whereas the cointegrating relationship for periods two and three are stable around a value of approximately two. Interestingly, this suggests that there is a structural break in the cointegrating relationship, but that not period two but period one is different from the remaining two. We could try to mitigate this by adding a dummy to the cointegrating relationship for the first period, or modelling only the second and third period.

Cointegrating Equation

	1 lag	2 lags
Constant	78.29	91.75
Trend	0.25*	0.20*
	(0.16)	(0.11)
EUA_{-1}	1	1
CER_{-1}	0.31	0.00
	(0.57)	(0.42)
OIL_{-1}	0.48***	0.39***
	(0.13)	(0.10)
$IND27_{-1}$	-1.34**	-1.37***
	(0.62)	(0.46)

Error Correction

	1 lag				2 lags			
variable	D(EUA)	D(CER)	D(OIL)	D(IND27)	D(EUA)	D(CER)	D(OIL)	D(IND27)
Constant	-0.07	-0.17	0.09	0.28***	-0.17	-0.27**	0.53	0.34***
	(0.15)	(-0.17)	(0.09)	(0.28)	(0.18)	(0.13)	(0.61)	(0.10)
EC	-0.08*	-0.07**	-0.53***	-0.09***	-0.05	-0.00	-0.88***	-0.12***
	(0.04)	(0.03)	(0.14)	(0.02)	(0.06)	(0.04)	(0.21)	(0.04)
$D(EUA_{-1})$	-0.38*	-0.04	0.16	-0.04	-0.46**	-0.13	0.31	-0.08
	(0.19)	(0.13)	(0.66)	(0.10)	(0.22)	(0.15)	(0.72)	(0.12)
$D(CER_{-1})$	0.34	-0.03	-0.94	0.28	0.35	0.01	-0.84	0.36
	(0.28)	(0.20)	(0.96)	(0.15)	(0.30)	(0.21)	(1.01)	(0.17)
$D(OIL_{-1})$	0.03	0.03	0.21*	-0.03	0.01	0.01	0.29**	-0.02
	(0.03)	(0.02)	(0.12)	(0.23)	(0.04)	(0.03)	(0.13)	(0.02)
$D(IND27_{-1})$	-0.16	-0.21	-0.35	-0.47***	0.01	0.02	-1.61*	-0.58***
	(0.23)	(0.17)	(0.81)	(0.13)	(0.29)	(0.20)	(0.98)	(0.16)
$D(EUA_{-2})$					-0.13	-0.07	0.39	-0.10
					(0.21)	(0.15)	(0.71)	(0.11)
$D(CER_{-2})$					0.14	0.12	0.09	0.29*
					(0.32)	(0.22)	(1.06)	(0.17)
$D(OIL_{-2})$					0.04	0.01	-0.10	0.00
					(0.04)	(0.26)	(0.13)	(0.02)
$D(IND27_{-2})$					0.26	0.42	-1.71	-0.31
					(0.26)	(0.18)	(0.88)	(0.15)
Statistics								
R^2	0.13	0.10	0.25	0.31	0.18	0.19	0.31	0.32
Log-likelihood	-393.60				-375.96			
AIC	12.61				12.76			
BIC	13.57				14.25			

Table 17: *VECM estimation results for levels, estimation period April 2009 until December 2014.*

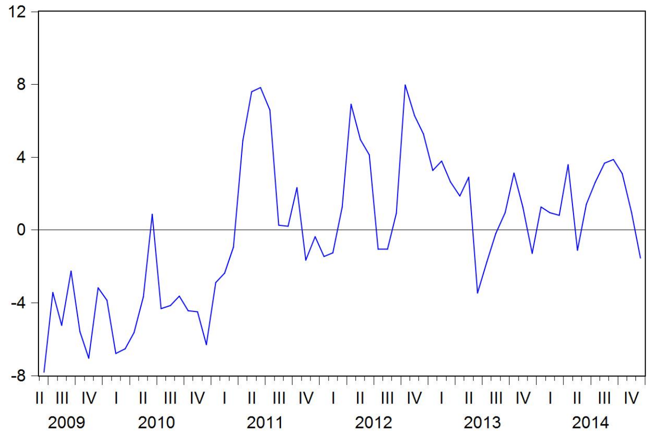


Figure 9: *Equilibrium deviations for the VECM with one lag and regular levels, estimation period April 2009 until December 2014.*

Next, I focus on the trend term, which is conceivably a very important aspect of the VECM. The model I estimate is specified as:

$$\Delta \boldsymbol{x}_t = \boldsymbol{\alpha}(\boldsymbol{\beta}, \boldsymbol{\beta}_0, \boldsymbol{\beta}_1) \begin{pmatrix} \mathbf{x}_{t-1} \\ \mathbf{1} \\ \mathbf{t} \end{pmatrix} + \boldsymbol{\gamma}_0 + \boldsymbol{\gamma}_1 t + \sum_{i=1}^{p} \boldsymbol{\Pi}_i \Delta \boldsymbol{x}_{t-i} + \boldsymbol{\varepsilon}_t$$

with $\boldsymbol{\gamma}_1 = \mathbf{0}$. Although the trends in the data suggest that involving a trend term in the cointegrating relationship is a good step, there are two main reasons why this specific specification could be suboptimal. Firstly, the trend of the cointegrating term, although often significant, has a confusing interpretation and the direction of its effect does not appear robust. Secondly, the trends in the carbon prices have shown significant breaks, and not accounting for this could lead to inefficient and wrong results.

Therefore, I estimate four additional models. The first model will not include the trend term in the cointegrating equation, only allowing for a trend in levels (that is, I set $\boldsymbol{\beta}_1 = \mathbf{0}$ as well, resulting in case 3 of the five standard model specifications discussed in Section 3.2). The second model will not include any trends at all (setting $\boldsymbol{\gamma}_0 = \boldsymbol{\beta}_1 = \boldsymbol{\gamma}_1 = \mathbf{0}$, resulting in case 2). The third model will be an extension of the first, but adds an exogenous dummy variable as a constant, selecting the second period. This model is given by Equation 17.

$$\Delta \boldsymbol{x}_t = \boldsymbol{\alpha}(\boldsymbol{\beta}, \boldsymbol{\beta}_0, \boldsymbol{\beta}_1) \begin{pmatrix} \mathbf{x}_{t-1} \\ \mathbf{1} \\ \mathbf{t} \end{pmatrix} + \boldsymbol{\gamma}_0 + \boldsymbol{\gamma}_D \mathbb{I}[26 < t < 46] + \boldsymbol{\gamma}_1 t + \sum_{i=1}^{p} \boldsymbol{\Pi}_i \Delta \boldsymbol{x}_{t-i} + \boldsymbol{\varepsilon}_t \quad (17)$$

with $\mathbb{I}[A]$ an indicator function that is equal to one if A is true and zero otherwise. In this case, the indicator function is one for values of t between 26 (May 2011) and 46 (January 2013). This model allows for a different trend in levels in the second period, during which we know the carbon prices experience a steep decline. Finally, I estimate the third model again but this time disregarding the first period. This serves to investigate the break visible in the cointegrating relationship of the previous model at the end of the first period.

Estimation results for the four models are presented in Tables 18 and 19.

The first model shows quite some similarity to the previous model, although now IND27 is no longer significant in the cointegrating vector but CER is. All error correction terms remain significant, and all significant variables have the same signs meaning that for those relations that remain significant their effect is unaltered. All VAR terms are also nearly identical. Finally, the R^2 for the carbon prices are also the same, although for oil it is slightly higher in the new model specification and for industrial production it is slightly lower. Information criteria both favour the new model, but it is safe to say that the inclusion or exclusion of a trend term in the cointegrating vector does not have a very strong effect.

The second model has a similar cointegrating vector as the first model, but has no significance for the carbon prices' error correction terms. As a result of this, the EUA and CER R^2 values are markedly lower than the first or the original model. I conclude that this model is a deterioration for the modelling of carbon prices, even though the BIC favours this model overall due to the relative parsimony.

The third model has the most interesting changes compared to the original model. The cointegrating vector is now significant for all variables, although the emission reductions no longer have a significant error correction term. For the rest, all significant signs have remained unchanged, further underlining the robustness of modelled VECMs. The most interesting results, however, is the strong significant parameter found for the dummy variable selecting the second period. This shows that the model is able to capture the strong decline in levels for the carbon prices. One would expect the constant parameters to then account for the positive trend in period 1 and 3, especially for EUA, but this is not the case. This could be due to the interference of the dummy, or simply because these trends are already captured by the error correction or VAR terms. This third model also strongly improves the values of R^2 for the two carbon prices, while the values for the other two variables remain similar. This strengthens the hypothesis that this model is better able to cope with the identified structural breaks in the carbon prices, and I use this model as the new base case. The cointegrating relationship is shown in Figure 10a. As with the previous model, we finds some visual proof for a structural break after the first period, but the effect is less clear with the new model specification. The first period again clearly centres a lower mean than the other two periods, but now there appears to be a slight trend in the cointegrating relationship in the second period. Impulse response is presented in Figure 11. Impulse response graphs show the way the values of variable change as a response to innovations or shocks of other variables. The impulse response graphs confirm that in our model the carbon prices do not react strongly to the other variables, as is indicated by the lack of significance of their error correction terms. The carbon allowances do react to a shock in the oil price, but the emission reductions barely respond to either the oil price and industrial production. Conversely, both OIL and IND27 show strong reactions to shocks in the carbon prices, which goes against economic intuition.

The third model estimated excluding the first period differs from the last model in several important ways. First, the cointegrating relationship is different in the sense that the emission reductions are no longer significant. Also, the dummy term nor the constant is significant for the EUA, whereas they both are for CER. This is surprising, as the EUA price shows a clear decline in the second period and a strong rise in the third. The error correction terms for the carbon prices are both highly significant and the signs now equal the signs for the OIL and IND27 cointegrating terms, which is in line with results we found previously. The error correction terms for OIL and IND27 themselves are no longer significant. These results better fit the economic interpretation that the carbon prices should do most of the adjusting as they are of less economic relevance. The VAR terms of the shorter model are generally similar to the terms in the longer one. The most interesting change, however, is the stark increase in R^2 for the carbon prices. Compared to the longer model this is unsurprising, as it is generally easier to fit a short model than a longer one. The R^2 for the EUA is higher than the sub-period estimations made at the beginning of this section, which is surprising. The CER also outperforms its period II estimate, but is much less compared to the remarkably high R^2 we found in the third period. This shorter model also has a slightly higher R^2 for IND27 compared to model three, but a much lower one for OIL. Figure 10b shows the cointegrating relationship for the shorter model. We notice high values at the beginning of the period, but from 2012 onwards the graph seems stable. The high values in the beginning of the period could be due to the fact that the short model does not appear to quite capture the structural break with the dummy trend term. Impulse response is presented in Figure 12. As expected, this model indicates that the two carbon prices react significantly to shocks in the other two variables, where the other two variables react to the carbon prices less strongly. In particular, both the EUA and CER prices react most strongly to innovations in the oil price, and slightly less so to innovations in the industrial production. Also, CER prices again appear to be dependent on innovations in EUA prices, and not the other way around. In absolute terms the response for carbon allowances is stronger than for emission reductions, but this can largely be explained by the higher value of allowance prices. This also explains the larger responses of the oil price. Industry has relatively small responses if we take into account industrial production values, but is a much less volatile variable.

Overall this last, shorter model appears to perform best. It has strong error correction terms for the carbon prices, which fits our intuition that if there is an equilibrium the carbon prices should do the brunt of the error correcting because of their relative importance to the other two variables. Also, the signs for the error correction terms and the cointegrating vector terms make economic sense because they suggest that a booming economic situation, indicated by a relatively high oil price and industrial production, cause increases in the carbon prices. The impulse response confirms these results, and indicate that shocks in both the oil price and industrial production affect both carbon prices. Finally, Figure 13 shows the variance decomposition for this model. Naturally, the variance of a variable in a certain period is almost exclusively caused by a shock in the variable itself, but as over time the variables influence one another the share of a variable's variance explained by other variables rises. Again, we notice that the oil price is the most important variable to explain the carbon prices' volatilities, and industrial production is very relevant also.

Cointegrating Equation

	model 1	model 2
Constant	11.43	12.36 (19.47)
EUA_{-1}	1	1
CER_{-1}	-0.69*** (0.10)	-0.75*** (0.11)
OIL_{-1}	0.21*** (0.06)	0.20*** (0.07)
$IND27_{-1}$	-0.32 (0.21)	-0.33 (0.23)

Error Correction

	model 1				model 2			
variable	D(EUA)	D(CER)	D(OIL)	D(IND27)	D(EUA)	D(CER)	D(OIL)	D(IND27)
Constant	-0.08 (0.15)	-0.18 (0.11)	-0.03 (0.55)	0.26*** (0.08)				
EC	-0.15* (0.07)	-0.11** (0.05)	-0.76*** (0.26)	-0.18*** (0.04)	-0.06 (0.06)	-0.02 (0.04)	-0.48** (0.22)	-0.17*** (0.03)
$D(EUA_{-1})$	-0.34* (0.19)	-0.01 (0.14)	0.31 (0.69)	0.00 (0.10)	-0.41** (0.19)	-0.09 (0.14)	0.05 (0.69)	-0.00 (0.09)
$D(CER_{-1})$	0.26 (0.28)	-0.01 (0.20)	0.31 (1.00)	0.00 (0.15)	0.38 (0.27)	0.04 (0.20)	-0.94 (0.98)	0.19 (0.14)
$D(OIL_{-1})$	0.03 (0.03)	0.03 (0.02)	0.20* (0.13)	-0.03 (0.02)	0.02 (0.04)	0.02 (0.03)	0.16 (0.13)	-0.03* (0.02)
$D(IND27_{-1})$	-0.14 (0.23)	-0.19 (0.16)	0.05 (0.83)	-0.47*** (0.12)	-0.10 (0.23)	-0.15 (0.17)	0.12 (0.84)	-0.47*** (0.12)
Statistics								
R^2	0.13	0.10	0.19	0.34	0.09	-0.02	0.15	0.35
Log-likelihood	-393.93				-399.41			
AIC	12.59				12.67			
BIC	13.52				13.49			

Table 18: *VECM estimation results for models 1 and 2, estimation period April 2009 until December 2014.*

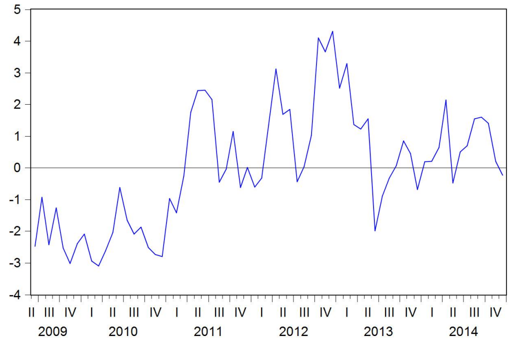
Cointegrating Equation

	model 3 original	model 3 short
Constant	20.95	273.43
EUA_{-1}	1	1
CER_{-1}	-0.74***	0.41
	(0.11)	(0.31)
OIL_{-1}	0.17**	-0.40**
	(0.07)	(0.17)
$IND27_{-1}$	-0.38*	-2.45***
	(0.21)	(0.87)

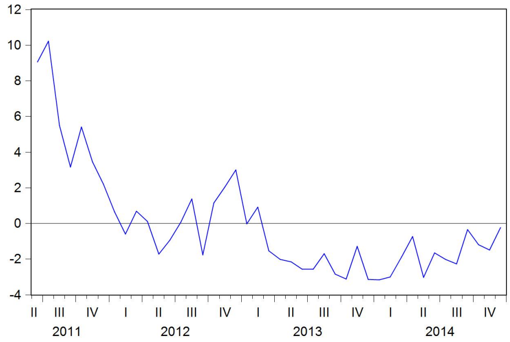
Error Correction

	model 3 original				model 3 short			
variable	D(EUA)	D(CER)	D(OIL)	D(IND27)	D(EUA)	D(CER)	D(OIL)	D(IND27)
Constant	-0.07	0.06	-0.27	0.37***	-0.30	-0.19*	-1.05	0.17
	(0.18)	(0.12)	(0.67)	(0.10)	(0.22)	(0.10)	(1.07)	(0.13)
Dummy	-0.59*	-0.90***	1.01	-0.39*	-0.11	-0.44***	0.21	-0.52
	(0.38)	(0.25)	(1.37)	(0.20)	(0.40)	(0.17)	(1.89)	(0.23)
EC	-0.13*	-0.03	-1.03***	-0.17***	-0.22***	-0.12***	0.13	0.03
	(0.09)	(0.06)	(0.34)	(0.05)	(0.06)	(0.02)	(0.27)	(0.03)
$D(EUA_{-1})$	-0.32*	0.01	0.36	0.02	-0.21	0.08	-0.08	-0.07
	(0.19)	(0.13)	(0.70)	(0.10)	(0.20)	(0.09)	(0.96)	(0.11)
$D(CER_{-1})$	0.14	-0.27	-1.24	0.11	-0.11	-0.25	-1.36	0.05
	(0.28)	(0.19)	(1.04)	(0.15)	(0.44)	(0.19)	(2.10)	(0.25)
$D(OIL_{-1})$	0.03	0.03	0.19	-0.03	-0.08*	-0.04**	0.12	-0.05**
	(0.03)	(0.02)	(0.12)	(0.02)	(0.04)	(0.02)	(0.20)	(0.02)
$D(IND27_{-1})$	-0.18	-0.21	0.01	-0.48***	-0.02	-0.09	1.10	-0.40***
	(0.18)	(0.12)	(0.66)	(0.10)	(0.23)	(0.10)	(1.07)	(0.13)
Statistics								
R^2	0.17	0.25	0.21	0.37	0.39	0.57	0.09	0.45
Log-likelihood	-384.82				-222.20			
AIC	12.44				11.82			
BIC	13.50				13.13			

Table 19: *VECM estimation results for both estimates of model 3, estimation period April 2009 until December 2014 for the original model and June 2011 until December 2014 for the shorter one.*



(a) *Equilibrium deviations for model 3, estimation period April 2009 until December 2014.*



(b) *Equilibrium deviations for model 3, estimation period June 2011 until December 2014.*

Figure 10: Equilibrium deviations for model 3 VECM with one lag.

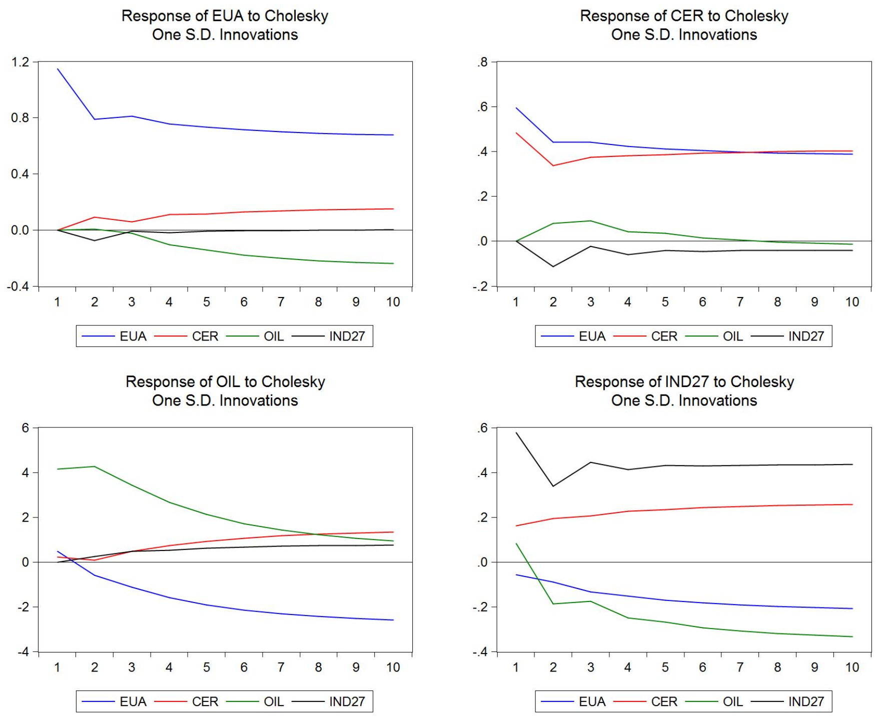


Figure 11: *Impulse responses for model 3, estimation period April 2009 until December 2014.*

Before we move on, I briefly investigate the robustness of the model and the validity of the results thus far. I do this by estimating the third model two more times. Once, leaving out the CER series, and the other time leaving out the EUA series. Results are presented in Appendix 7.3 Table 30.

OIL remains highly significant in the cointegrating vector, but is the only variable

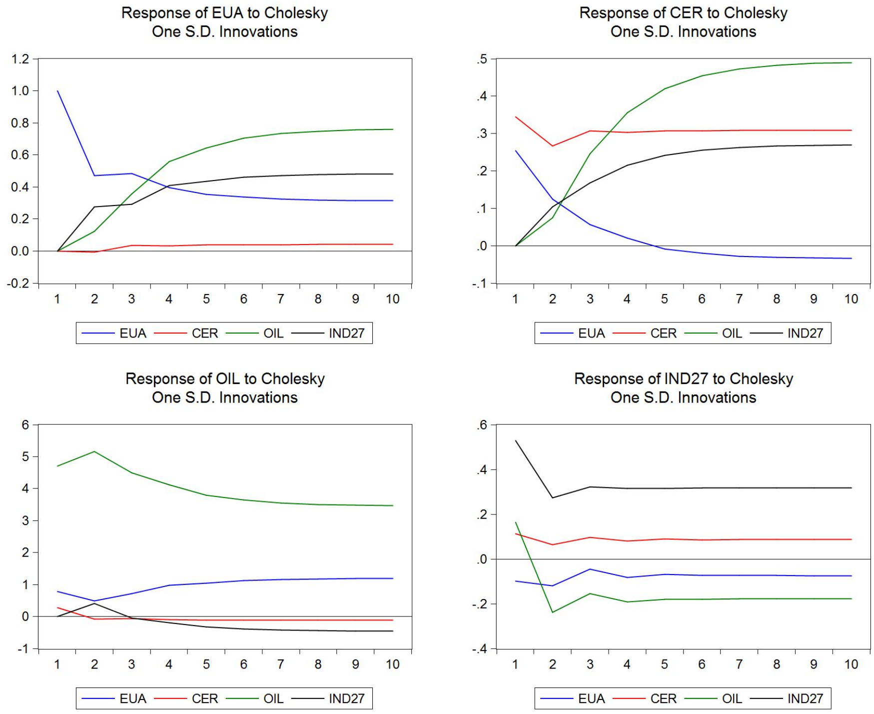


Figure 12: *Impulse responses for model 3, estimation period June 2011 until December 2014.*

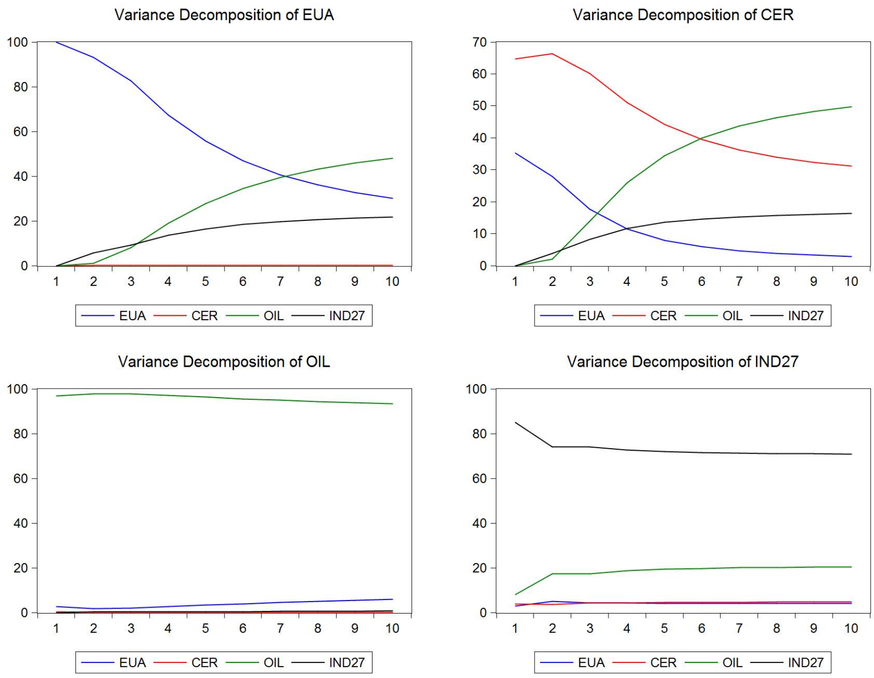


Figure 13: *Variance decomposition for model 3, estimation period June 2011 until December 2014.*

to do so. Neither EUA nor CER has a significant error correction term, but OIL and IND27 do. This is surprising, as it suggests that taken individually the carbon prices do not actively restore the equilibria, but the other variables do. Contrary to these results, there is no economic reason that could suggest that the oil price or industrial production is reliant on the carbon price but not the other way around. The R^2 for the carbon prices is slightly lower than the model including both series, but higher than all previous model specifications. This strengthens the view that the Dummy, which is again significant in these two models, is of importance for the coping with the structural breaks in the carbon prices. In conclusion, although no economic validity can be given to the apparent result that the carbon prices are individually weakly exogenous, the results of these two models are not problematically different from the combined one even though it is clearly best to model EUA and CER together.

5.3.3 Energy and Economy models

This section presents the estimation results of the more extensive energy and economy models. Given the results so far, I estimate them with the specifications of model 3 and use as a first estimation date both April 2009 and June 2011. The models estimated from April 2009 onwards are presented here, the results for the shorter models are shown in Appendix 7.3 Tables 32 and 33. The energy model has one cointegrating relationship, and I estimate this model twice in the model specifications for model 3: once including the TEMP variable and once including TEMPD. I find that the model with TEMP performs best, so these results are discussed in detail. Results for the model with the TEMPD variable can be found in Appendix 7.3 Table 31. The economic model includes the credit spread as an exogenous variable, and has two cointegrating relationships. Results are presented in Tables 20 and 21 and for the energy and economy model respectively.
The energy model estimated over the entire period shows very high significance for all variables in the cointegrating relationship. Unfortunately, this is not the case for the error correction terms and both carbon prices have an insignificant term. Only the oil and gas price are shown to react to errors in the equilibrium. Again we find that the dummy is significant for both carbon prices, whereas the constant is not. Also, we find several significant VAR terms, although not all of them make economic sense. For example, both the gas and coal prices seem to significantly react to both the lagged carbon allowance and certified emission reduction price differences, but the signs for the two carbon prices are not equal. The temperature variable shows significance for the carbon prices at the 10% significance level. Comparing these

results to the results found for the model only including the oil price and industrial production, we find a higher R^2, meaning that this economy model is better able to capture the variation of the carbon prices than the previous model. Also, this VECM on the prices outperforms the VAR we estimated for the returns previously. The results are quite different if we estimate this model starting at June 2011. Several variables in the cointegrating relationship have changed signs, and their parameters are much larger than they were previously. The latter can be explained by a lower EUA price over this period, scaling up the parameters in the normalisation. In this model the oil and electricity prices have a significant error correction term, but both are small. The sign for the OIL error correction term has remained the same, meaning that the oil price now has a different relationship compared to the variables that changed signs in the cointegrating relationship. All other parameters remain roughly comparable to the parameters found for the model estimated from April 2009 onwards. Overall, it does not seem like the shorter model is an improvement compared to the longer one.
Figure 14 shows the cointegrating relationship of this model over time. We notice that there does not appear to be a significant break between the first and second period, further reinforcing the idea that the shorter model has little value in this instance. Figure 15 shows the impulse response graphs for the two carbon prices. As expected, the two carbon prices barely react to shocks in the other variables, and again the EUA price reacts only to itself whereas the CER price reacts to both itself and the EUA price.

Cointegrating Equation

Constant	31.78
EUA_{-1}	1
CER_{-1}	-1.31*** (0.17)
OIL_{-1}	-0.41*** (0.07)
GAS_{-1}	30.72*** (5.32)
$COAL_{-1}$	0.18*** (0.06)
$ELEC_{-1}$	-0.67*** (0.67)

Error Correction

variable	D(EUA)	D(CER)	D(OIL)	D(GAS)	D(COAL)	D(ELEC)
Constant	0.09	0.02	-0.33	0.01	0.64	0.26
	(0.17)	(0.11)	(0.58)	(0.01)	(0.63)	(0.55)
Dummy	-0.68*	-0.88***	1.39	-0.03	-2.26*	-0.27
	(0.36)	(0.25)	(1.24)	(0.02)	(1.36)	(1.19)
EC	-0.00	0.02	1.01***	-0.01***	-0.23	-0.15
	(0.06)	(0.04)	(0.19)	(0.00)	(0.21)	(0.19)
$D(EUA_{-1})$	-0.39**	-0.05	-0.72	0.04***	1.40*	0.91
	(0.19)	(0.13)	(0.67)	(0.01)	(0.72)	(0.63)
$D(CER_{-1})$	0.25	-0.22	0.19	-0.06***	-2.09*	-1.23
	(0.29)	(0.19)	(0.98)	(0.01)	(1.07)	(0.94)
$D(OIL_{-1})$	0.02	0.02	0.21*	-0.00	-0.00	0.04
	(0.03)	(0.02)	(0.11)	(0.00)	(0.12)	(0.11)
$D(GAS_{-1})$	-7.07**	-3.01	-21.12**	0.06	2.68	-6.06
	(2.99)	(2.03)	(10.19)	(0.15)	(11.22)	(9.80)
$D(COAL_{-1})$	0.03	-0.02	-0.08	0.00**	-0.02	0.25**
	(0.03)	(0.02)	(0.12)	(0.00)	(0.14)	(0.12)
$D(ELEC_{-1})$	0.05	0.05	0.46**	-0.00	0.08	-0.03
	(0.05)	(0.04)	(0.20)	(0.00)	(0.22)	(0.19)
$D(TEMP_{-1})$	0.16*	0.10*	0.39	-0.01**	-0.93**	-0.38
	(0.10)	(0.07)	(0.33)	(0.00)	(0.36)	(0.31)
Statistics						
R^2	0.25	0.30	0.38	0.34	0.18	0.13
Log-likelihood	-549.07					
AIC	18.36					
BIC	20.53					

Table 20: *VECM estimation results for energy model 3, estimation period April 2009 until December 2014.*

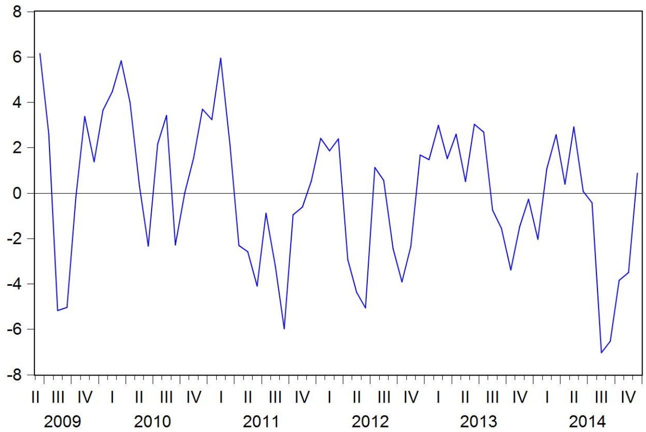


Figure 14: *Equilibrium deviations for energy model 3, estimation period April 2009 until December 2014.*

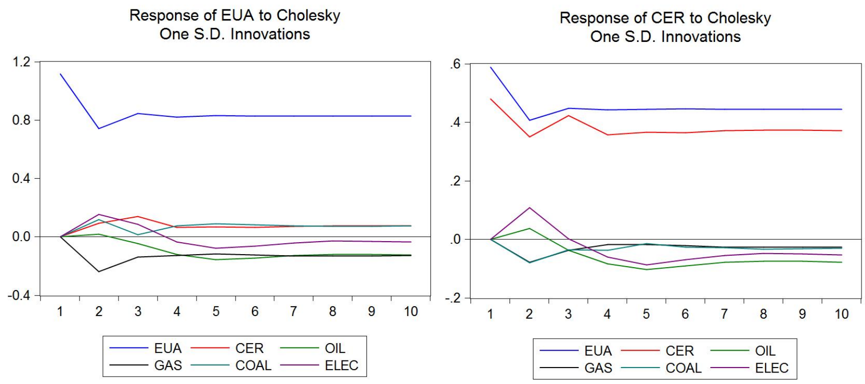


Figure 15: *Impulse response for energy model 3 with one lag and regular levels for the period April 2009 until December 2014.*

The economy model is modelled with two cointegrating vectors, but surprisingly the estimated cointegrating relationships are basically identical. The three variables that have a significant error correction term are EUA, STOXX50, and USD. They do not appear to be actually error correcting, as their parameters for the first and second cointegrating relationship seem to cancel out. The dummy variable is not significant for the carbon prices, but EUA has a significant constant term. The VAR terms show low significance for the carbon series, but seem more effective for the other variables. CREDIT is significant for the EUA, however. Although the error correction aspect of the model appears not to be functioning, the R^2 for the carbon prices is higher in this model compared to the equivalent energy model. The R^2 is naturally also higher than the R^2 of the model only including OIL and IND27 and

the VAR model for the returns.
The estimation results for the period starting in June 2011 are similar. Again, the two error correction terms seem to balance the two similar cointegrating relationships out. The dummy parameter for EUA has turned significant, but the constant lost significance. The sign of the dummy variable is positive, which should not be the case as the dummy was introduced specifically to capture the negative trend in the carbon prices in period between June 2011 and December 2012. The VAR terms in this shorter model are comparable to the terms in the longer model.
Figure 16 shows the cointegrating relationship for the economy model. Again, we find no visual break between the first and second period for this model, meaning that there is no real reason to estimate from June 2011 onwards. Figure 17 shows the impulse response graphs for the two carbon prices. These graphs are comparable to previous results, although the carbon prices now seem to react more strongly to other variables, indicating that this model does capture some carbon price dynamics.

Cointegrating Equation

Constant	-204.93	-229.26
EUA_{-1}	1	0
CER_{-1}	0	1
$STOXX50_{-1}$	-0.02 (0.01)	-0.01 (0.01)
$IND27_{-1}$	0.76 (0.88)	0.85 (0.88)
$TERM_{-1}$	-27.01*** (4.51)	-30.13*** (4.52)
USD_{-1}	168.22*** (38.35)	170.74*** (38.48)

Error Correction

variable	D(EUA)	D(CER)	D(STOXX50)	D(IND27)	D(TERM)	D(USD)
Constant	-1.38* (0.75)	-0.63 (0.51)	195.03** (76.36)	-0.36 (0.47)	-0.03 (0.11)	0.02 (0.03)
Dummy	0.35 (0.53)	-0.54 (0.36)	-116.44** (53.92)	-0.56* (0.33)	-0.31*** (0.07)	-0.01 (0.02)
EC 1	-0.31** (0.15)	-0.06 (0.10)	59.44*** (14.94)	-0.07 (0.09)	-0.01 (0.02)	0.01** (0.01)
EC 2	0.26* (0.14)	0.04 (0.10)	-58.49*** (14.59)	0.06 (0.09)	0.02 (0.02)	-0.01** (0.01)
$D(EUA_{-1})$	-0.34* (0.19)	-0.02 (0.13)	-30.07 (18.87)	-0.06 (0.12)	0.05** (0.03)	-0.01 (0.01)
$D(CER_{-1})$	0.20 (0.28)	-0.18 (0.19)	52.47* (28.56)	0.11 (0.17)	-0.03 (0.04)	0.01 (0.01)
$D(STOXX50_{-1})$	0.00 (0.00)	0.00* (0.00)	0.20 (0.16)	0.00 (0.00)	0.00* (0.00)	0.00 (0.00)
$D(IND27_{-1})$	-0.29 (0.22)	-0.31** (0.15)	-43.05* (22.13)	-0.48*** (0.14)	-0.06* (0.03)	-0.01 (0.01)
$D(TERM_{-1})$	-0.42 (0.89)	-0.65 (0.60)	26.01 (90.29)	-0.24 (0.55)	0.27** (0.12)	0.02 (0.03)
$D(USD_{-1})$	-4.56 (4.94)	-4.82 (3.34)	-490.96 (502.87)	-2.17 (3.08)	-1.37* (0.70)	-0.01 (0.18)
$D(CREDIT_{-1})$	0.52* (0.31)	0.25 (0.21)	-60.58* (31.56)	0.32* (0.19)	0.05 (0.04)	-0.01 (0.01)
Statistics						
R^2	0.32	0.36	0.39	0.28	0.42	0.22
Log-likelihood	-407.10					
AIC	14.48					
BIC	17.05					

Table 21: *VECM estimation results for economy model 3, estimation period April 2009 until December 2014.*

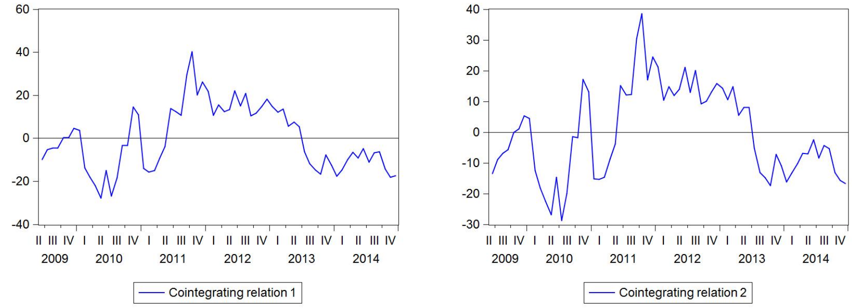


Figure 16: *Equilibrium deviations for economy model 3, estimation period April 2009 until December 2014.*

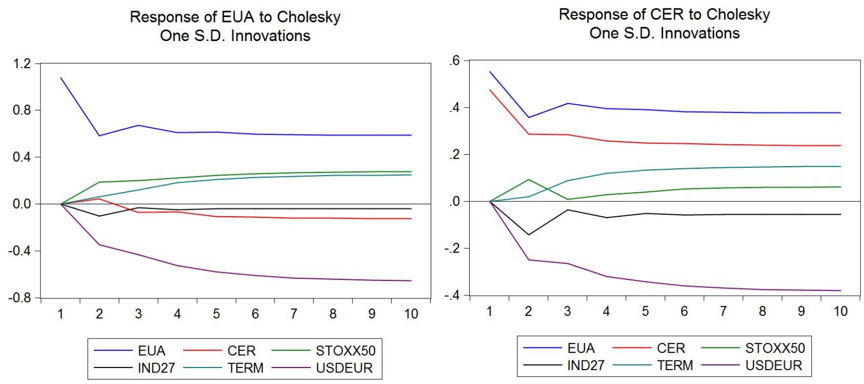


Figure 17: *Impulse response for economy model 3, estimation period April 2009 until December 2014.*

Because of the malfunctioning error correction specification for the economy models I also estimate the economy model with only one cointegrating relationship. Results for the estimation starting from April 2009 are presented in Table 22. These results are more promising. In the cointegrating vector, only IND27 is insignificant. STOXX50, TERM and USD have significant error correction terms, but unfortunately the carbon series do not. The dummy variables for the carbon prices are significant and negative, in line with expectation. The VAR terms remained almost unchanged. Naturally, the R^2 has decreased, and the AIC also favours the model with two cointegrating relationships, but the BIC does not. When estimating two relationships, the error correction terms cancelled each other. Because of this and the BIC, I consider it best to estimate the economy model with only one cointegrating vector. Figures 18 and 19 show the cointegrating relationship and impulse response graphs respectively. The cointegrating relationship is stable over the entire period. The impulse response again shows that the CER reacts to the EUA, but not the other way around. Shocks in the other variables impact the carbon prices little, mainly because of their insignificant error correction terms. The USD/EUR exchange rate seems to have the largest impact on the carbon prices, which could be explained by the strong significant VAR term founds for USD.

Cointegrating Equation

Constant	44.49
EUA_{-1}	1
CER_{-1}	-1.09*** (0.08)
$STOXX50_{-1}$	-0.01*** (0.00)
$IND27_{-1}$	-0.17 (0.13)
$TERM_{-1}$	5.77*** (0.95)
USD_{-1}	-17.52*** (5.42)

Error Correction

variable	D(EUA)	D(CER)	D(STOXX50)	D(IND27)	D(TERM)	D(USD)
Constant	0.15	-0.09	60.88	-0.09	-0.23***	0.01
	(0.41)	(0.26)	(41.14)	(0.24)	(0.06)	(0.01)
Dummy	-0.77*	-0.94***	-18.01	-0.76***	-0.16***	0.00
	(0.14)	(0.26)	(41.14)	(0.24)	(0.06)	(0.01)
EC	0.03	0.06	29.87***	-0.01	-0.05***	0.01**
	(0.10)	(0.07)	(10.45)	(0.06)	(0.01)	(0.00)
$D(EUA_{-1})$	-0.38*	-0.04	-26.12	-0.07	0.06**	-0.01
	(0.20)	(0.13)	(19.78)	(0.12)	(0.03)	(0.01)
$D(CER_{-1})$	0.28	-0.15	45.60	0.13	-0.04	0.01
	(0.30)	(0.19)	(29.91)	(0.17)	(0.04)	(0.01)
$D(STOXX50_{-1})$	0.00*	0.00***	0.05	0.00	0.00	0.00
	(0.00)	(0.00)	(0.15)	(0.00)	(0.00)	(0.00)
$D(IND27_{-1})$	-0.16	-0.27*	-54.73**	-0.45***	-0.07**	-0.01
	(0.23)	(0.15)	(22.81)	(0.13)	(0.03)	(0.01)
$D(TERM_{-1})$	-1.04	-0.87	80.53	-0.35	0.35***	0.03
	(0.92)	(0.59)	(92.45)	(0.54)	(0.13)	(0.03)
$D(USD_{-1})$	-8.79*	-6.31*	-118.26	-2.93	-0.83	0.01
	(5.08)	(3.25)	(507.75)	(2.95)	(0.71)	(0.17)
$D(CREDIT_{-1})$	-0.02	0.06	-12.96*	0.22	0.12***	-0.00
	(0.27)	(0.17)	(27.29)	(0.15)	(0.04)	(0.01)
Statistics						
R^2	0.21	0.34	0.32	0.27	0.35	0.21
Log-likelihood	-421.01					
AIC	14.54					
BIC	16.71					

Table 22: *VECM estimation results for economy model 3 with only one cointegrating relationship, estimation period April 2009 until December 2014.*

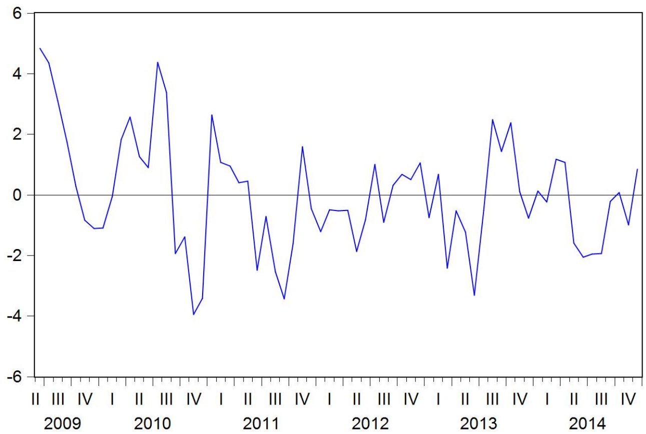


Figure 18: *Equilibrium deviations for economy model 3 with one cointegrating relationship, estimation period April 2009 until December 2014.*

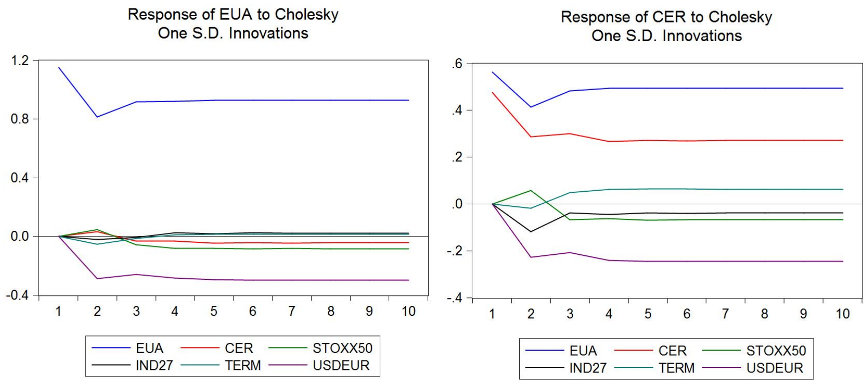


Figure 19: *Impulse response for economy model 3 with one cointegrating relationship, estimation period April 2009 until December 2014.*

This section has been an exercise to determine the best way to model the carbon price dynamics. The results for the energy and economy models indicate that there is not much merit in trying to capture carbon price relationships in large models. The non carbon variables share strong relationships that appear to dominate the VECM specifications, and the potential relationship with the carbon terms is of less importance. The results we find modelling only the oil price and industrial production are more useful. Due to the smaller number of variables the relationship between the carbon prices and the other variables is more important, and the VECM is able to yield significant results. Because of the limited importance of carbon credits in global markets it is therefore best to model them in small models opposed to larger ones. The issue of structural breaks in this model is important, as the cointegrating graph shows a visual break between the first period and the latter two.

These breaks were not visible in the larger models. Because we expect structural breaks due to changes in the carbon price dynamics, the limited importance of the carbon series can explain the lack of structural breaks for the energy and economy models. It has been shown beneficial to include trend dummy variables to cope with the decline in the carbon prices during phase II, although a visual break in the cointegrating relationship around June 2011 remains. For future research, it would be interesting to see how other ways of coping with structural breaks could improve these results.

6 Conclusion

This thesis finds promising results for the modelling of the long-term dynamics of the carbon prices. Although the political aspect of the supply side of carbon credits is and will remain to be large and influential, I find substantial proof indicating that carbon credits are functioning securities in international markets with anticipated relationships with economic indicators. This is an important result, as it suggests that carbon credits are already partly functioning in the way they are intended to. This could also show policy makers in which ways carbon credits can best be utilised.
I study the carbon price dynamics using various models. In the body of carbon literature the most popular model is the vector autoregressive model. I use this VAR model to analyse the dynamics between carbon returns and differences of other variables, but find little to no significant results. A vector error correction model on the carbon prices performs much better. In fact, the presence of cointegration indicates that a VAR model in this instance can be seen as misspecified, in the sense that it does not account for the present long-term equilibrium. For VECMs, an important consideration is that the strongest shared equilibria between all included variables is modelled. In models with a large number of variables this is shown to result in an insignificant role for carbon credits; the model fails to capture their dynamics accurately. However, this effect does not occur in smaller models. I find that VECM modelling of carbon prices and a small number of other variables can yield strong results that provide clear economic insights.
Specifically, the oil price and European industrial production are shown to share a long-term equilibrium with both carbon price series. If either the oil price or industrial production are relatively high, disturbing the equilibrium, the carbon prices increase and correct for the error in the equilibrium. For industrial production this makes economic sense: if industrial production is high then so must be the demand for carbon credits as industrial producers produce emissions for their operations.

The oil price has a less clear interpretation. Conventionally, rising oil prices are thought to coincide with a reduction in economic activity. Baumeister and Hamilton (2015) argue that this generally holds, although they demonstrate that only price increases due to supply shocks lead to an economic reduction in the long run, whereas price shocks due to demand shocks do not. On the other hand, Hooker (1996) shows that after 1973 the oil price appears to no longer Granger cause the U.S. economic indicators. Instead, a high oil price can be thought to be caused by a growing demand for oil in a growing economy, which would also necessitate higher carbon prices. It is this latter effect that appears relevant to the current carbon dynamics, as I find a positive relationship between the oil and carbon prices in almost all estimated models. Finally, the carbon allowances seem to have a strong effect on the emission reductions but not the other way around, which is expected due to the regulated relative importance of the two carbon credits. The CERs are also shown to behave very similar to the EUAs with regards to the other variables. This result was expected due to their similar role in the carbon markets, but also uncertain considering their strong and persistent decline in price during 2011.

What this means for the short-term value of carbon credits is not entirely clear, however. The estimated models include data up to December 2014. Since then, the oil price has shown a remarkable decline, which would suggest that carbon price should also have declined. However, the decline of the oil price appears to mainly be a politically driven event, instead of an economically driven one. The supply effects of oil production seem to currently dominate the price level, through the introduction of shale, OPEC's influence, and the Iran-U.S. nuclear deal. The demand for oil also plays a role, but mainly through China's slowing growth and shifting economy. Therefore, this price decline does not necessarily tell us anything about the carbon prices given our interpretation of the role of the oil price in the models. Instead, the recent modest economic and industrial growth in Europe could partially explain the small rise in carbon prices since 2014.

I also find some interesting results that are more focussed on the details of carbon price modelling. First, the period of study (April 2009 - December 2014) shows some proof of the presence of two structural breaks, one occurring around June 2011 and the second at the start of the phase III, or January 2013. During this period the carbon series show a strong negative trend, whereas overall they appear to be gently rising. After correcting for the negative trend in the middle period using a dummy variable, the estimated equilibrium still saw a break around June 2011. Because of this, modelling carbon dynamics starting at this date yields the best results. Secondly, I find proof of heteroskedasticity in the carbon prices with a higher price resulting in an increased volatility. This can theoretically be accounted for by imposing a logarithmic transformation, but I find that this does not improve results. Finally, I show that there is no merit in including more than one lag to the VECMs, as the number of parameters to be estimated in such models rapidly increases without tangible results.

As one of the first studies to focus on the long-term dynamics of carbon credits, and of CERs in general, results are all still introductory. This thesis can be built on in several ways. Firstly, VECMs with a small number of variables could be estimated in a similar manner using different variables than the oil price and industrial production. I selected OIL and IND27 as they were promising variables and appeared useful for an initial analysis. Several other energy, economy, and weather variables have also been shown as promising candidates for carbon modelling. Secondly, it would be very interesting to cope with the apparent structural break in the cointegrating relationship at June 2011 by allowing for the cointegration parameters to change over time. Specifically, I propose that the methodology introduced by Hansen (2003) is applied. Due to time constraints this has not been possible for this thesis, but it could be a much more elegant solution to the problem of a break than the discarding of the period April 2009 - May 2011 done by me. Related to this issue is the third suggestion: that the linear models set forth in this thesis be extended to nonlinear models such as regime switching ones. Nonlinear models have by others been demonstrated to be much more effective at capturing the short-term dynamics of carbon prices, and therefore prove promising to model their long-term equilibria also. Fourthly, the recent emerging of several other carbon markets around the world is to be studied to investigate if they show similar dynamics as the EU ETS, and determine if there are any relationships between the various carbon prices. Fifthly, the influence of oil on carbon prices could be studied in more detail. The results in this thesis depend on the interpretation of oil as a sort of economic indicator, in which the oil price rises due to an increase of demand in strong economies. This is not a conventional interpretation of the oil price's role, although it has intuitive merit. Further analysis of the oil and carbon connection can clarify this issue, and is particularly interesting given the present volatile situation of oil. Finally, additional studies on the supply side effect of the carbon prices would be valuable. The supply of carbon credits on the EU ETS is thought to have a great impact on their prices, but the effect is still not entirely understood nor has the supply side been compared to the demand side studied in this thesis. It would be interesting to see how both sides are jointly able to model the carbon dynamics.

Overall, the modelling of long-term carbon dynamics is demonstrated to be a promising field of research and will continue to be extremely relevant. I am confident that additional research can shed even more light on the workings of the carbon prices, benefiting policy makers, industrial producers, and emission reducing initiatives alike. Policy makers can use insights on carbon price dynamics to determine the best price range for carbon credits. I demonstrate that carbon prices react to economic conditions. Ideally an increase in economic activity is reflected in the carbon prices in such a way that there is a negative feedback to industrial producers, giving them an incentive to find the most efficient ways of reducing carbon emissions. The value of carbon credits will always be highly dependent on the exact regulatory environment, but correctly managing the supply side of the credits could make them effective and efficient tools for curtailing global carbon emissions.

7 Appendix

7.1 DATA

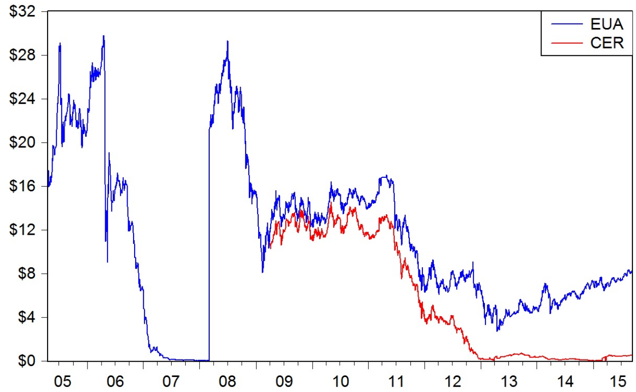


Figure 20: *Daily settlement prices EUA and CER futures. End date is 11/09/2015 and series start at 04/22/2005 and 01/04/2009 for the EUA and CER respectively.*

7.2 VAR

	Energy	
variable	EUA	CER
Constant	0.00	0.12***
	(0.02)	(0.02)
EUA_{-1}	-0.34***	-0.51*
	(0.13)	(0.27)
CER_{-1}	0.12**	0.29**
	(0.06)	(0.13)
OIL_{-1}	-0.20	1.05*
	(0.29)	(0.62)
$COAL_{-1}$	0.42	-0.59
	(0.32)	(0.69)
GAS_{-1}	-0.37*	0.02
	(0.21)	(0.45)
$ELEC_{-1}$	0.04	-0.41
	(0.32)	(0.69)
$TEMPD_{-1}$	-0.02	-0.20**
	(0.04)	(0.10)
Statistics		
R^2	0.23	0.22
Log-likelihood	399.74	
AIC	-10.35	
BIC	-8.78	

Table 23: *Parameter estimation results for the VAR Energy TEMPD model, estimation period April 2009 - December 2014.*

7.3 VECM

Cointegrating Equation

	1 lag	2 lags
Constant	35.67	90.53
Trend	0.10 (0.08)	0.18** (0.08)
EUA_{-1}	1	1
CER_{-1}	-5.59*** (1.42)	-2.47* (1.50)
OIL_{-1}	-4.31*** (1.09)	-6.71*** (1.13)
$IND27_{-1}$	-1.76 (13.80)	-13.54 (12.94)

Error Correction

	1 lag				2 lags			
variable	D(EUA)	D(CER)	D(OIL)	D(IND27)	D(EUA)	D(CER)	D(OIL)	D(IND27)
Constant	0.02 (0.02)	0.02 (0.02)	0.03 (0.01)	0.01 (0.00)	-0.01 (0.02)	-0.01 (0.03)	0.02 (0.03)	0.00 (0.00)
EC	0.05 (0.05)	0.06 (0.05)	0.13*** (0.03)	0.00 (0.00)	-0.13*** (0.04)	-0.09* (0.05)	0.04 (0.04)	0.00 (0.00)
$D(EUA_{-1})$	-0.44 (0.44)	-0.17 (0.43)	0.03 (0.24)	0.01 (0.04)	-1.33*** (0.39)	-0.81 (0.53)	0.07 (0.44)	-0.01 (0.05)
$D(CER_{-1})$	0.35 (0.47)	-0.01 (0.46)	0.24 (0.26)	0.01 (0.04)	0.48 (0.36)	0.07 (0.48)	-0.21 (0.39)	0.02 (0.04)
$D(OIL_{-1})$	0.16 (0.29)	0.30 (0.28)	0.05 (0.16)	0.00 (0.02)	0.02 (0.21)	0.20 (0.28)	0.11 (0.23)	0.01 (0.02)
$D(IND27_{-1})$	-2.99 (2.73)	-3.75 (2.69)	-1.03 (1.49)	-0.37* (0.23)	0.28 (2.06)	-1.23 (2.81)	-0.85 (2.29)	-0.29 (0.25)
$D(EUA_{-2})$					-0.95*** (0.34)	-0.51 (0.46)	0.14 (0.37)	-0.07* (0.04)
$D(CER_{-2})$					0.49 (0.34)	0.23 (0.47)	-0.24 (0.38)	0.07* (0.04)
$D(OIL_{-2})$					-0.08 (0.23)	-0.14 (0.32)	0.05 (0.26)	0.01 (0.03)
$D(IND27_{-2})$					6.43*** (2.20)	5.68* (3.00)	0.70 (2.47)	0.20 (0.26)
Statistics								
R^2	0.22	0.31	0.61	0.15	0.72	0.53	0.28	0.39
Log-likelihood	210.49				222.06			
AIC	-15.12				-15.40			
BIC	-13.70				-13.18			

Table 24: *VECM estimation results for logarithmic levels, estimation period April 2009 until May 2011.*

Cointegrating Equation

	1 lag	2 lags
Constant	748.07	-526.45
Trend	-0.00 (0.05)	-0.10* (0.05)
EUA_{-1}	1	1
CER_{-1}	1.11* (0.68)	-2.44*** (0.86)
OIL_{-1}	-11.04*** (1.40)	12.21*** (2.03)
$IND27_{-1}$	-152.05*** (21.83)	103.22*** (38.38)

Error Correction

	1 lag				2 lags			
variable	D(EUA)	D(CER)	D(OIL)	D(IND27)	D(EUA)	D(CER)	D(OIL)	D(IND27)
Constant	-0.09* (0.05)	-0.20*** (0.05)	0.02 (0.02)	-0.00 (0.00)	-0.02 (0.06)	-0.08 (0.06)	0.01 (0.01)	-0.00 (0.00)
EC	-0.11 (0.07)	-0.25*** (0.08)	0.06*** (0.02)	0.00 (0.00)	-0.13 (0.12)	-0.02 (0.12)	-0.12*** (0.03)	-0.00 (0.01)
$D(EUA_{-1})$	-0.21 (0.34)	0.07 (0.37)	-0.15 (0.11)	-0.01 (0.01)	-0.06 (0.44)	-0.33 (0.44)	0.13 (0.11)	0.00 (0.02)
$D(CER_{-1})$	-0.11 (0.24)	-0.15 (0.27)	0.07 (0.08)	0.01 (0.01)	-0.27 (0.32)	0.08 (0.32)	-0.19** (0.08)	-0.00 (0.01)
$D(OIL_{-1})$	-1.30 (1.01)	-2.62** (1.13)	0.80** (0.32)	-0.04 (0.04)	-0.32 (1.11)	-1.15 (1.12)	0.87*** (0.29)	-0.05 (0.05)
$D(IND27_{-1})$	-6.91 (6.47)	-13.22* (7.22)	6.06*** (2.08)	-0.04 (0.25)	24.62 (17.04)	23.54 (17.07)	12.37* (4.39)	-0.32 (0.72)
$D(EUA_{-2})$					0.08 (0.71)	-0.03 (0.72)	0.13 (0.18)	-0.02 (0.03)
$D(CER_{-2})$					-0.04 (0.87)	-0.20 (0.87)	-0.11 (0.228)	0.02 (0.04)
$D(OIL_{-2})$					2.65* (1.59)	1.70 (1.59)	0.79* (0.41)	-0.00 (0.07)
$D(IND27_{-2})$					15.85* (9.46)	28.55*** (9.48)	3.86 (2.44)	-0.10 (0.40)
Statistics								
R^2	0.30	0.54	0.44	0.53	0.43	0.70	0.71	0.53
Log-likelihood	149.68				165.23			
AIC	-12.07				-12.02			
BIC	-10.62				-9.78			

Table 25: *VECM estimation results for logarithmic levels, estimation period June 2011 until December 2012.*

Cointegrating Equation

	1 lag	2 lags
Constant	5.59	-9.28
Trend	-0.02***	-0.01***
	(0.01)	(0.00)
EUA_{-1}	1	1
CER_{-1}	0.19***	0.21*
	(0.03)	(0.02)
OIL_{-1}	-3.32***	-3.05***
	(0.40)	(0.33)
$IND27_{-1}$	1.85	4.80*
	(3.95)	(2.73)

Error Correction

	1 lag				2 lags			
variable	D(EUA)	D(CER)	D(OIL)	D(IND27)	D(EUA)	D(CER)	D(OIL)	D(IND27)
Constant	0.01	-0.16***	-0.02	0.00	0.03	-0.16***	-0.00	0.00
	(0.04)	(0.05)	(0.01)	(0.00)	(0.06)	(0.05)	(0.02)	(0.00)
EC	-0.07	-2.71***	-0.04	-0.00	0.15	-3.00***	0.02	-0.01
	(0.26)	(0.31)	(0.09)	(0.01)	(0.38)	(0.35)	(0.13)	(0.01)
$D(EUA_{-1})$	-0.33	1.26***	-0.04	-0.00	-0.50	2.09***	-0.12	0.01
	(0.29)	(0.34)	(0.10)	(0.01)	(0.48)	(0.44)	(0.16)	(0.01)
$D(CER_{-1})$	0.14	-0.20	-0.01	-0.00	0.20*	-0.23*	0.00	-0.00
	(0.11)	(0.13)	(0.04)	(0.00)	(0.13)	(0.11)	(0.04)	(0.00)
$D(OIL_{-1})$	-0.71	-4.01***	0.08	-0.03	-0.29	-4.72***	0.29	-0.03
	(0.98)	(1.17)	(0.33)	(0.03)	(1.35)	(1.24)	(0.46)	(0.03)
$D(IND27_{-1})$	0.05	0.02	0.29	-0.63***	-7.19	6.60	-2.97	-0.85***
	(6.97)	(8.35)	(2.38)	(0.20)	(10.79)	(9.88)	(3.64)	(0.27)
$D(EUA_{-2})$					-0.19	0.84**	-0.10	0.01
					(0.39)	(0.36)	(0.13)	(0.01)
$D(CER_{-2})$					-0.04	-0.10	0.03	0.00
					(0.13)	(0.12)	(0.04)	(0.00)
$D(OIL_{-2})$					0.53	-0.05	0.13	-0.01
					(1.22)	(1.12)	(0.41)	(0.03)
$D(IND27_{-2})$					-7.59	-11.44	-4.17	-0.48*
					(9.70)	(8.88)	(3.27)	(0.25)
Statistics								
R^2	0.25	0.84	0.06	0.45	0.31	0.91	0.16	0.63
Log-likelihood	159.86				178.70			
AIC	-10.91				-11.14			
BIC	-9.48				-8.93			

Table 26: *VECM estimation results for logarithmic levels, estimation period January 2013 until December 2014.*

Cointegrating Equation

	1 lag	2 lags
Constant	-27.99	-57.29
Trend	-0.23 (0.19)	-0.46*** (0.17)
CER_{-1}	1	1
EUA_{-1}	-0.17 (0.20)	0.66*** (0.21)
OIL_{-1}	0.12*** (0.04)	0.24*** (0.04)
$IND27_{-1}$	0.14 (0.31)	0.47* (0.29)

Error Correction

	1 lag		2 lags	
variable	D(CER)	D(EUA)	D(CER)	D(EUA)
Constant	0.19 (0.30)	0.25 (0.34)	-0.19 (0.43)	-0.17 (0.36)
EC	-0.40 (0.32)	-0.39 (0.37)	0.37 (0.30)	0.77*** (0.25)
$D(CER_{-1})$	-0.01 (0.46)	0.37 (0.53)	-0.13 (0.49)	0.23 (0.41)
$D(EUA_{-1})$	-0.13 (0.38)	-0.42 (0.44)	-0.51 (0.45)	-1.06*** (0.38)
$D(OIL_{-1})$	0.07 (0.06)	0.06 (0.07)	0.06 (0.07)	0.03 (0.06)
$D(IND27_{-1})$	-0.47 (0.35)	-0.42 (0.40)	-0.27 (0.37)	-0.12 (0.31)
$D(CER_{-2})$			0.16 (0.48)	0.45 (0.40)
$D(EUA_{-2})$			-0.38 (0.42)	-0.86** (0.35)
$D(OIL_{-2})$			0.00 (0.07)	0.01 (0.06)
$D(IND27_{-2})$			0.65* (0.40)	0.82** (0.34)
Statistics				
R^2	0.34	0.24	0.51	0.70
Log-likelihood	-123.15		-96.60	
AIC	12.68		12.31	
BIC	14.10		14.54	

Table 27: *VECM estimation results for carbon prices, estimation period April 2009 until June 2011 and normalised around CER.*

Cointegrating Equation

	1 lag	2 lags
Constant	-54.61	50.59
Trend	-0.17* (0.09)	0.23*** (0.17)
CER_{-1}	1	1
EUA_{-1}	-0.81*** (0.08)	-0.61*** (0.04)
OIL_{-1}	0.24*** (0.04)	-0.10*** (0.03)
$IND27_{-1}$	0.30 (0.37)	-0.49** (0.21)

Error Correction

	1 lag		2 lags	
variable	D(CER)	D(EUA)	D(CER)	D(EUA)
Constant	-1.11*** (0.33)	-1.26* (0.64)	-0.54* (0.31)	-0.50 (0.68)
EC	0.42** (0.20)	0.69* (0.39)	-0.92* (0.57)	0.15 (0.12)
$D(CER_{-1})$	-1.10* (0.68)	-1.48 (1.30)	-0.15 (0.68)	-0.80 (1.49)
$D(EUA_{-1})$	0.57 (0.37)	0.54 (0.72)	-0.01 (0.43)	0.33 (0.96)
$D(OIL_{-1})$	-0.06 (0.04)	-0.09 (0.09)	-0.12 (0.06)	-0.09 (0.14)
$D(IND27_{-1})$	0.04 (0.25)	0.13 (0.47)	0.30 (0.53)	1.34 (1.17)
$D(CER_{-2})$			0.08 (0.62)	-0.11 (1.37)
$D(EUA_{-2})$			0.02 (0.37)	0.19 (0.81)
$D(OIL_{-2})$			0.00 (0.08)	0.19 (0.18)
$D(IND27_{-2})$			0.61* (0.32)	0.84 (0.71)
Statistics				
R^2	0.25	0.25	0.46	0.27
Log-likelihood	-92.73		-68.82	
AIC	12.81		11.98	
BIC	14.25		14.22	

Table 28: *VECM estimation results for carbon prices, estimation period July 2011 until December 2012 and normalised around CER.*

Cointegrating Equation

	1 lag	2 lags
Constant	-10.15	-13.30
Trend	-0.02* (0.01)	-0.09* (0.05)
CER_{-1}	1	1
EUA_{-1}	0.30*** (0.05)	0.78*** (0.23)
OIL_{-1}	-0.02* (0.01)	0.03 (0.05)
$IND27_{-1}$	0.11 (0.08)	0.12 (0.31)

Error Correction

	1 lag		2 lags	
variable	D(CER)	D(EUA)	D(CER)	D(EUA)
Constant	-0.03* (0.01)	0.11 (0.18)	0.02 (0.02)	-0.21 (0.16)
EC	-0.47*** (0.06)	0.09 (0.79)	-0.07* (0.04)	-1.33 (0.32)
$D(CER_{-1})$	-0.08 (0.12)	2.95* (1.54)	0.04 (0.16)	1.08 (1.27)
$D(EUA_{-1})$	0.07*** (0.02)	-0.42* (0.25)	-0.04 (0.03)	0.46* (0.26)
$D(OIL_{-1})$	-0.01 (0.00)	-0.02 (0.05)	0.01** (0.00)	-0.02 (0.04)
$D(IND27_{-1})$	0.02 (0.02)	0.05 (0.31)	-0.06* (0.04)	0.37 (0.29)
$D(CER_{-2})$			0.26** (0.12)	-3.47*** (0.95)
$D(EUA_{-2})$			-0.07*** (0.02)	0.26 (0.18)
$D(OIL_{-2})$			0.01*** (0.00)	0.06* (0.04)
$D(IND27_{-2})$			-0.07* (0.04)	0.20 (0.28)
Statistics				
R^2	0.83	0.32	0.80	0.71
Log-likelihood	-68.69		-52.46	
AIC	8.14		8.12	
BIC	9.56		10.33	

Table 29: *VECM estimation results for carbon prices, estimation period January 2013 until December 2014 and normalised around CER.*

Cointegrating Equation

	EUA	CER
Constant	-43.97	71.04
EUA_{-1}	1	
CER_{-1}		1
OIL_{-1}	4.49*** (1.26)	-3.48*** (1.19)
$IND27_{-1}$	-2.95 (5.38)	1.78 (5.11)

Error Correction

	EUA			CER		
variable	D(EUA)	D(OIL)	D(IND27)	D(CER)	D(OIL)	D(IND27)
Constant	0.11 (0.18)	-0.30 (0.68)	0.34*** (0.09)	0.07 (0.12)	-0.23 (0.67)	036*** (0.09)
Dummy	-0.85** (0.37)	1.41 (1.38)	-0.39* (0.19)	-0.97*** (0.25)	0.63 (1.38)	-0.39** (0.19)
EC	0.00 (0.00)	-0.03*** (0.01)	-0.01*** (0.00)	-0.00 (0.00)	0.03** (0.01)	0.01*** (0.00)
$D(EUA_{-1})$	-0.29** (0.12)	-0.60 (0.45)	0.03 (0.06)			
$D(CER_{-1})$				-0.28** (0.12)	-1.15* (0.67)	0.09 (0.09)
$D(OIL_{-1})$	0.02 (0.03)	0.19 (0.13)	-0.03 (0.02)	0.03 (0.02)	0.17 (0.13)	-0.03* (0.02)
$D(IND27_{-1})$	-0.03 (0.21)	-0.20 (0.81)	-0.43*** (0.11)	-0.17 (0.14)	0.44 (0.81)	-0.44*** (0.11)
Statistics						
R^2	0.14	0.16	0.37	0.24	0.16	0.38
Log-likelihood		-347.30			-318.00	
AIC		10.99			10.12	
BIC		11.69			10.81	

Table 30: *VECM estimation results for models excluding EUA and CER, estimation period April 2009 until December 2014.*

Cointegrating Equation

Constant	39.21
EUA_{-1}	1
CER_{-1}	-1.47*** (0.21)
OIL_{-1}	-0.51*** (0.09)
GAS_{-1}	35.66*** (6.45)
$COAL_{-1}$	0.23*** (0.08)
$ELEC_{-1}$	-0.77*** (0.12)

Error Correction

variable	D(EUA)	D(CER)	D(OIL)	D(GAS)	D(COAL)	D(ELEC)
Constant	0.16	0.05	0.16	0.00	-0.06	0.04
	(0.18)	(0.13)	(0.60)	(0.01)	(0.68)	(0.60)
Dummy	-0.69*	-0.90***	1.62	-0.03	-2.29*	-0.29
	(0.37)	(0.25)	(1.20)	(0.02)	(1.38)	(1.20)
EC	-0.01	0.01	0.87***	-0.01***	-0.17	-0.11
	(0.05)	(0.03)	(0.15)	(0.18)	(0.15)	(0.15)
$D(EUA_{-1})$	-0.37*	-0.03	-0.71	0.03***	1.30*	0.85
	(0.19)	(0.13)	(0.63)	(0.01)	(0.72)	(0.63)
$D(CER_{-1})$	0.20	-0.26	0.25	-0.06***	-1.93*	-1.14
	(0.29)	(0.20)	(0.93)	(0.01)	(1.07)	(0.93)
$D(OIL_{-1})$	0.02	0.02	0.24**	-0.00	-0.02	0.03
	(0.03)	(0.02)	(0.11)	(0.00)	(0.13)	(0.11)
$D(GAS_{-1})$	-6.57**	-2.55	-22.29**	0.02	1.54	-6.82
	(3.02)	(2.05)	(9.75)	(0.15)	(11.18)	(9.75)
$D(COAL_{-1})$	0.05	0.05	-0.13	0.01***	0.05	0.28**
	(0.04)	(0.03)	(0.12)	(0.00)	(0.14)	(0.12)
$D(ELEC_{-1})$	0.05	0.05	0.50**	-0.00	0.07	-0.03
	(0.06)	(0.04)	(0.20)	(0.00)	(0.22)	(0.20)
$D(TEMPD_{-1})$	-0.33	-0.14	-2.54**	0.01	3.23**	1.05
	(0.36)	(0.24)	(1.16)	(0.01)	(1.33)	(1.16)
Statistics						
R^2	0.23	0.27	0.42	0.31	0.17	0.12
Log-likelihood	-550.02					
AIC	18.39					
BIC	20.56					

Table 31: *VECM estimation results for energy model 3 TEMPD, estimation period April 2009 until December 2014.*

Cointegrating Equation

Constant	3870.74
EUA_{-1}	1
CER_{-1}	30.02*** (11.23)
OIL_{-1}	-7.14*** (5.33)
GAS_{-1}	1587.82*** (277.28)
$COAL_{-1}$	-12.89*** (4.76)
$ELEC_{-1}$	-63.83*** (6.74)

Error Correction

variable	D(EUA)	D(CER)	D(OIL)	D(GAS)	D(COAL)	D(ELEC)
Constant	-0.07 (0.24)	-0.07 (0.12)	-1.88 (0.99)	0.00 (0.01)	-0.65 (0.79)	-0.14 (0.76)
Dummy	-0.06 (0.43)	-0.57*** (0.22)	1.15 (1.80)	0.01 (0.02)	0.11 (1.44)	1.54 (1.38)
EC	0.00 (0.00)	0.00 (0.00)	0.01*** (0.00)	0.00 (0.00)	0.00 (0.00)	0.01** (0.00)
$D(EUA_{-1})$	-0.41* (0.24)	0.04 (0.12)	-0.13 (0.98)	0.02 (0.01)	-0.26 (0.79)	0.36 (0.76)
$D(CER_{-1})$	0.76 (0.53)	-0.10 (0.27)	-2.34 (2.19)	-0.01 (0.03)	0.93 (1.77)	-0.00 (1.69)
$D(OIL_{-1})$	0.00 (0.04)	-0.00 (0.02)	0.07 (0.16)	-0.00 (0.00)	-0.09 (0.13)	-0.02 (0.12)
$D(GAS_{-1})$	-6.85* (3.85)	-0.71 (1.93)	4.17 (15.91)	-0.21 (0.22)	-1.97 (12.79)	2.50 (12.25)
$D(COAL_{-1})$	0.12** (0.06)	0.04 (0.03)	0.29 (0.23)	0.01* (0.00)	-0.18 (0.18)	0.54*** (0.18)
$D(ELEC_{-1})$	0.06 (0.07)	0.02 (0.03)	0.23 (0.29)	0.00 (0.00)	0.26 (0.23)	0.22 (0.22)
$D(TEMP_{-1})$	0.24* (0.14)	0.04 (0.07)	0.82 (0.56)	-0.01 (0.01)	-0.03 (0.45)	-0.04 (0.43)
Statistics						
R^2	0.36	0.37	0.27	0.27	0.11	0.30
Log-likelihood	-306.46					
AIC	17.32					
BIC	20.03					

Table 32: *VECM estimation results for energy model 3, estimation period June 2011 until December 2014.*

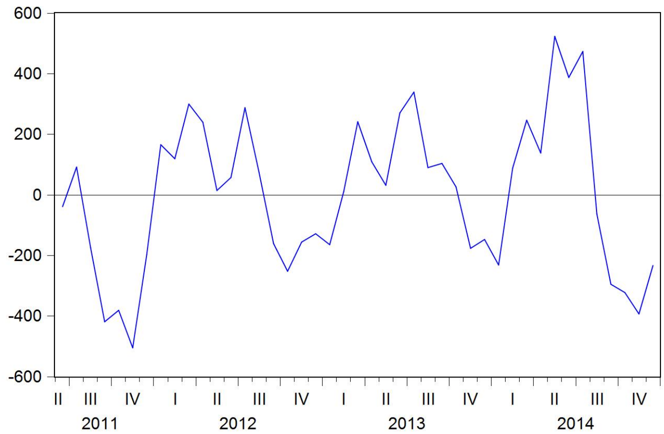


Figure 21: *Equilibrium deviations for energy model 3, estimation period June 2011 until December 2014.*

Cointegrating Equation

Constant	57.54	103.31
EUA_{-1}	1	0
CER_{-1}	0	1
$STOXX50_{-1}$	0.03*** (0.01)	0.06*** (0.01)
$IND27_{-1}$	-2.45** (1.23)	-3.98** (1.79)
$TERM_{-1}$	-13.99*** (3.34)	-23.75*** (4.86)
USD_{-1}	98.61*** (20.66)	144.83*** (30.03)

Error Correction

variable	D(EUA)	D(CER)	D(STOXX50)	D(IND27)	D(TERM)	D(USD)
Constant	1.29 (1.37)	-0.17 (0.71)	500.46** (129.77)	0.19 (1.11)	-0.39* (0.24)	0.16 (0.04)
Dummy	1.26** (0.62)	-0.06 (0.32)	-183.94*** (58.43)	-0.59 (0.50)	-0.21* (0.11)	-0.01 (0.02)
EC 1	-0.68*** (0.14)	-0.29*** (0.07)	32.72** (12.90)	0.04 (0.11)	0.01 (0.02)	0.00 (0.00)
EC 2	0.37*** (0.09)	0.17*** (0.05)	-30.12*** (8.68)	-0.02 (0.07)	-0.00 (0.02)	-0.00** (0.00)
D(EUA_{-1})	-0.23 (0.18)	0.08 (0.09)	-3.03 (16.71)	-0.12 (0.14)	0.02 (0.03)	0.00 (0.00)
D(CER_{-1})	-0.06 (0.38)	-0.21 (0.20)	-1.30 (36.10)	0.12 (0.31)	0.08 (0.07)	-0.02** (0.01)
D($STOXX50_{-1}$)	-0.00** (0.00)	-0.00 (0.00)	0.46*** (0.16)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
D($IND27_{-1}$)	0.13 (0.20)	-0.02 (0.11)	-88.45*** (19.16)	-0.53*** (0.16)	-0.09*** (0.04)	-0.01 (0.01)
D($TERM_{-1}$)	-1.27 (1.05)	-0.50 (0.55)	-68.59 (99.45)	-0.30 (0.85)	0.16 (0.18)	-0.00 (0.03)
D(USD_{-1})	9.65* (5.92)	3.31 (3.07)	-778.82 (559.42)	-3.85 (4.79)	-0.41 (1.04)	0.00 (0.16)
D($CREDIT_{-1}$)	-1.00 (0.66)	-0.08 (0.34)	-198.86*** (62.22)	0.00 (0.53)	0.23* (0.12)	-0.08*** (0.02)
Statistics						
R^2	0.61	0.60	0.70	0.30	0.45	0.62
Log-likelihood	-198.55					
AIC	12.86					
BIC	16.06					

Table 33: *VECM estimation results for economy model 3, estimation period June 2011 until December 2014.*

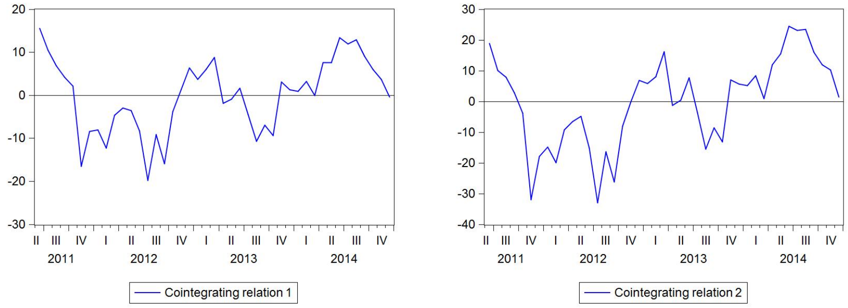


Figure 22: *Equilibrium deviations for economy model 3, estimation period June 2011 until December 2014.*

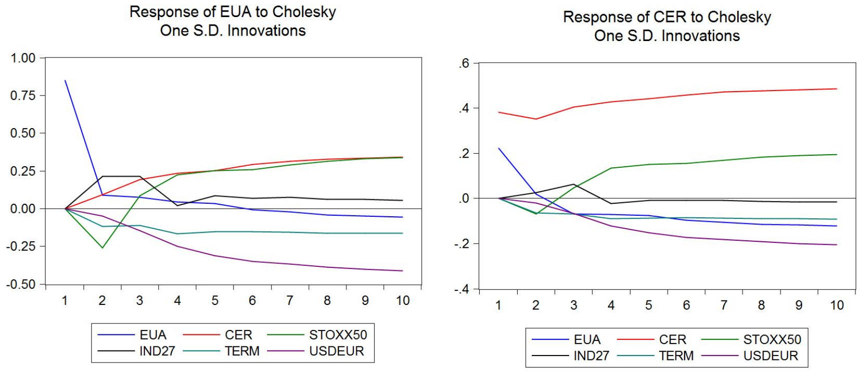


Figure 23: *Impulse response for economy model 3 with one lag and regular levels for the period April 2009 until December 2014.*

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