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EUAs and CERs: Interactions in a Markov regime-switching environment

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Abstract

This paper analyzes jointly the time series of European Union Allowances (EUAs) and Certified Emissions Reductions (CERs) in a Markov regime-switching environment. The purpose consists in capturing the interactions between the two time series - which have been highlighted in previous literature - with respect to the underlying business cycle. Given the recent period of economic growth and financial crisis, regime switching models appear indeed interesting to shed new light on the data. The main result of the paper features a switch from a low-growth period to a high-growth period in July 2009, in a context of timid economic recovery. Besides, the Markov regime-switching model reveals that significant interactions exist between EUAs (during expansions and recessions) and CERs (mostly during expansions). Collectively, these results could be of use to regulatory authorities, academics and financial agents (investment bankers, analysts, asset managers).

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1 Introduction

European Union Allowances (EUAs) and Certified Emissions Reductions (CERs) are fungible assets within the European Union Emissions Trading Scheme. Their properties have been documented by previous literature. First, Chevallier (2010) analyzes both time series in a vector autoregressive (VAR), impulse response function (IRF) and cointegrating framework. The author shows that EUAs and CERs affect each other significantly through the VAR model, and react quite rapidly to shocks on each other through the IRF analysis. Most importantly, both price series are found to be cointegrated, with EUAs leading the price discovery process in the long-term through the vector error-correction mechanism.

Second, Chevallier (2011) studies the time-varying correlations between the two assets in a Dynamic Conditional Correlation (DCC) GARCH model. The study confirms the presence of strong ARCH and GARCH effects, and documents correlations in the range of $[0.01;0.90]$ between EUAs and CERs. These findings can then be re-used by financial agents to reach optimal risk management, portfolio selection, and hedging strategies.

Third, Mansanet-Bataller et al. (2011) investigate the price differences between EUAs and sCERs, and the extent to which financial and industrial operators may benefit from arbitrage strategies by buying sCERs and selling EUAs (i.e. selling the EUA-sCER spread). The authors show that the spread is mainly driven by EUA prices and market microstructure variables, and less importantly by emissions-related fundamental drivers. This empirical analysis of emissions markets reveals the rational behavior of investors: profit-maximizing strategies are elaborated given the very unusual institutional characteristics of emissions markets.

Compared to previous literature, this paper provides the first assessment of the interactions between EUAs and CERs in a Markov regime-switching environment. Given the recent changes in the underlying business cycle (i.e. a conjunction of a financial crisis since late 2007 coupled with a timid economic recovery since 2010), this approach may be beneficial to three groups of agents. On the one hand, academics would benefit from a greater understanding of how the relationship between EUAs and CERs changes depending on economic activity. This literature has been documented for most energy markets (including the oil market), but to a lesser extent for the

carbon market.

On the other hand, regulatory authorities could also be interested in understanding how the price path of EUAs and CERs evolves during periods of economic recession/expansion. If the carbon market is to exhibit clear macroeconomic fundamentals, then the regulator needs to diminish its intervention by amending the allocation rules for instance.

Finally, analysts, investment bankers and portfolio managers are interested into the evolution of EUAs and CERs depending on the business cycle. Based on that information, they can formulate recommendations on buy/sell strategies, on the creation of new financial products, and on asset allocation strategies. If EUAs and CERs are found to be counter-cyclical for instance, then these emissions assets can be included for diversification purposes in a broad portfolio composed of equities, bonds and commodities.

Our main results highlight significant switches from low-growth to high-growth periods between the two time series, with the main regime switch being located in July 2009. Therefore, emissions assets are related to the underlying business cycle. Besides, EUAs affect CERs during expansions and recessions, while CERs are found to affect EUAs at statistically significant levels especially during expansions.

The rest of the paper is structured as follows. Section 2 summarizes the data used. Section 3 introduces the Markov regime-switching model. Section 4 presents the empirical results. Section 5 briefly concludes.

2 Data

Figure 1 presents the daily time series of EUA Futures prices traded in Euro/ton of CO₂ on the European Climate Exchange (ECX) from March 09, 2007 to April 26, 2011 which corresponds to a sample of 1,066 observations. The EUA Futures prices are also presented in logreturn transformation in the bottom panel of Figure 1.

Figure 2 presents the daily time series of CER Futures prices traded in Euro/ton of CO₂ on ECX. The start of the study periods corresponds to the trading of CER futures allowances on ECX. The CER Futures prices are also presented in logreturn transformation in the bottom panel of Figure 2.

3 Regime-switching model

Following Hamilton (1989), time series may be modelled by following different processes at different points in time, with the shifts between processes determined by the outcome of an unobserved Markov chain. In this framework, the presence of multiple regimes can be acknowledged using multivariate models where parameters are made dependent on a hidden state process. Consider an n -dimensional vector $\mathbf{y}_t \equiv (y_{1t}, \dots, y_{nt})'$ which is assumed to follow a VAR(p) with parameters:

$$\mathbf{y}_t = \boldsymbol{\mu}(s_t) + \sum_{i=1}^p \boldsymbol{\Phi}_i(s_t) y_{t-i} + \boldsymbol{\epsilon}_t \quad (1)$$

$$\boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}(s_t))$$

where the parameters for the conditional expectation $\boldsymbol{\mu}(s_t)$ and $\boldsymbol{\Phi}_i(s_t)$, $i = 1, \dots, p$, as well as the variances and covariances of the error terms $\boldsymbol{\epsilon}_t$ in the matrix $\boldsymbol{\Sigma}(s_t)$ all depend upon the state variable s_t which can assume a number q of values (corresponding to different regimes). Given initial values for the regime probabilities, and the conditional mean for each state, the log-likelihood function can be constructed and maximised numerically to obtain parameters estimates of the model.

The general idea behind the class of Markov-switching models is that the parameters and the variance of an autoregressive process depend upon an *unobservable* regime variable $s_t \in \{1, \dots, M\}$, which represents the probability of being in a particular state of the world. A complete description of the Markov-switching model requires the formulation of a mechanism that governs the evolution of the stochastic and unobservable regimes on which the parameters of the autoregression depend. Once a law has been specified for the states s_t , the evolution of regimes can be inferred from the data. Typically, the regime-generating process is an ergodic Markov chain with a finite number of states defined by the transition probabilities:

$$p_{ij} = \text{Prob}(s_{t+1} = j | s_t = i), \quad \sum_{j=1}^M p_{ij} = 1 \quad \forall i, j \in \{1, \dots, M\} \quad (2)$$

In such a model, the optimal inference about the unobserved state variable s_t would take the form of a probability. The transition probabilities of the Markov-process determines the probability that volatility will switch to another regime, and thus the expected duration of each regime. We rely on a constant specification to keep the model parsimonious. Each regime is thus the realization of a first-order Markov chain with constant transition probabilities.

By setting $S = [1 \ 1]$, both the autoregressive coefficients and the model's variance are switching according to the transition probabilities. Typically, we set the number of states M equal to 2. Therefore, state $M = 1$ represents the 'high growth' phase, whereas state $M = 2$ characterizes the 'low growth' phase (for more details, see Hamilton (2008) and references therein). When $M = 1$, the growth of the endogenous variable is given by the population parameter μ_1 , whereas when $M = 2$, the growth rate is μ_2 .

As M rises, it becomes increasingly easy to fit complicated dynamics and deviations from the normal distribution in the returns (Guidolin and Timmermann (2006)). However, this comes at the cost of having to estimate more parameters. As Bradley and Jansen (2004) put it, a well-known problem with any application of nonlinear models is the problem of overfitting. There is therefore a trade-off between the depth of the economic interpretation which one would have available with higher degrees for state variables, and the numerical difficulties which accompany such an effort.

The model is estimated based on Gaussian maximum likelihood with $S_t = 1, 2$. The calculation of the covariance matrix is performed using the second partial derivatives of the log likelihood function. \mathbf{P} is the transition matrix which controls the probability of a switch from state $M = 1$ to state $M = 2$:

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix}$$

The sum of each column in \mathbf{P} is equal to 1, since they represent the full probabilities of the process for each state.

4 Empirical results

4.1 Comments

Results are provided in Table 3. The statistically significant coefficients of the two means μ show the presence of switches between high-/low-growth periods. During expansion, output growth per month is equal to 0.21% on average. The time series is likely to remain in the expansionary phase with an estimated probability equal to 95%. Regime 1 is assumed to last 19 days on average. During recession, the average growth rate is equal to -0.29%. The probability that it will stay in recession is equal to 93%. The average duration of Regime 2 is 14 days. According to the ergodic probabilities, the time series would spend 60% (40%) of the time spanned by our data sample in Regime 1 (Regime 2).

Interestingly, other coefficient estimates suggest that EUAs have several statistically significant effects on EUAs: during Regime 1 (as $\phi_2 = 0.07$ is significant at the 5% level), and during Regime 2 (as $\phi_1 = 0.06$ and $\phi_2 = -0.06$ are significant at the 1% level). Therefore, these results confirm the insights by Chevallier (2010, 2011) concerning the significant impact of EUAs on CERs, since the EU ETS is the most developed emissions market in the world to date. Concerning CERs, we can notice that they impact EUAs essentially during expansionary phases (as $\phi_1 = 0.12$ and $\phi_2 = -0.21$ are significant at the 5% level).

The associated smoothed and regime probabilities¹ are shown in Figures 3 and 4, respectively. They reveal essentially two periods in the carbon futures markets: a low-growth period during March 2007-June 2009, and a high-growth period during July 2009-April 2011. The main switch from regime 2 to regime 1 occurs during July 2009, as the world economies start to recover from the financial crisis. Therefore, the Markov-switching model reveals new characteristics about the behaviour of emissions assets.

¹The estimation routine generates two by-products in the form of the regime and *smooth* probabilities. Recall that the *regime* probability at time t is the probability that state t will operate at t , conditional on information available *up to* $t - 1$. The other by-product is the *smooth* probability, which is the probability of a particular state in operation at time t conditional on *all information* in the sample. The smooth probability allows the researcher to ‘look back’ and observe how regimes have evolved overtime.

4.2 Diagnostic tests

The upper panel of Table 4 reports the results of three diagnostic tests. The first is a test of the Markov-switching model against the simple nested null hypothesis that the data follow a geometric random walk with i.i.d innovations. Note M the p -value from the LR test:

$$Prob[LR(q^*)] > M = Prob(\chi_d^2 > M) + \frac{VM^{(d-1)/2}e^{-M/2}2^{-d/2}}{\Gamma(d/2)} \quad (3)$$

where $Prob(LR(q^*) > M|H_0)$ is the upper bound critical value, LR is the likelihood ratio statistic, q^* is the vector of transition probabilities ($q^* = \operatorname{argmax} LnL(q)|H_1$) and d is the number of restrictions under the null hypothesis.

In Table 4, this adjustment produces a LR statistic equal to 26.75. We reject the random walk at the 0.1 percent level. We conclude that the relationship is better described by a two-regime Markov-switching model than by the random walk model.

The second test reported in Table 4 is for symmetry of the Markov transition matrix, which implies symmetry of the unconditional distribution of the growth rates. This test examines the maintained hypothesis that p (the probability of being in a high-growth state or boom) equals q (the probability of being in a low-growth state or depression) against the alternative that $p < q$. Table 4 reports statistics that are asymptotically standard normal under the null. We reject the hypothesis of symmetry at the 5% level.

Third, Ang and Bekaert (2002) set out a formal definition of and a test for regime classification. They argue that a good regime switching model should be able to classify regimes sharply. Weak regime inference implies that the regime-switching model cannot successfully distinguish between regimes from the behavior of the data, and may indicate misspecification. To measure the quality of regime classification, we therefore use Ang and Bekaert's (2002) Regime Classification Measure (RCM) defined for two states as:

$$RCM = 400 \times \frac{1}{T} \sum_{t=1}^T p_t(1 - p_t) \quad (4)$$

where the constant serves to normalize the statistic to be between 0

and 100, and p_t denotes the ex-post smoothed regime probabilities. Good regime classification is associated with low RCM statistic values. A value of 0 indicates that the two-regime model is able to perfectly discriminate between regimes, whereas a value of 100 indicates that the two-regime model simply assigns each regime a 50% chance of occurrence throughout the sample. Consequently, a value of 50 is often used as a benchmark (see Chan et al. (2011) for instance).

Adopting this definition to the current context, the RCM 2-State statistic is equal to 30.45 in Table 4. It is substantially below 50, consistent with the existence of two regimes. It is very interesting that our estimated Markov-switching model has classified the two regimes extremely well.

Finally, Table 4 reports the distributional characteristics for the Markov-switching processes implied by the estimates in Table 3. Compared to Tables 1 and 2, these values demonstrate that the two-regime model we employ matches quite well the first four central moments of the data. We conclude that the Markov-switching model produces both the degree of skewness and the amount of kurtosis that are present in the original data.

5 Conclusion

The main idea behind Markov regime-switching models consists in capturing the behavior of economic time series with respect to the underlying business cycle. Since the years 2007 to 2011 have been characterized by periods of economic growth and recession, it appears interesting to investigate how the interactions between EUAs and CERs - the two most fungible assets among emissions markets - evolve in this context.

This paper shows that significant interactions exist between the two markets, especially during periods of economic recession when the market trends are destabilised. Besides, EUAs and CERs seem to vary during two main periods from low-growth to high-growth, with the main regime switch occurring in July 2009 (in the recovery process from the financial crisis). Overall, the Markov-Switching modelling brings us new insights as to when market shocks occur, and actually impact the EUA and CER futures price series. Therefore, the results presented in this paper can be seen as complementary to the time-varying correlations between the two markets highlighted recently by Chevallier (2011).

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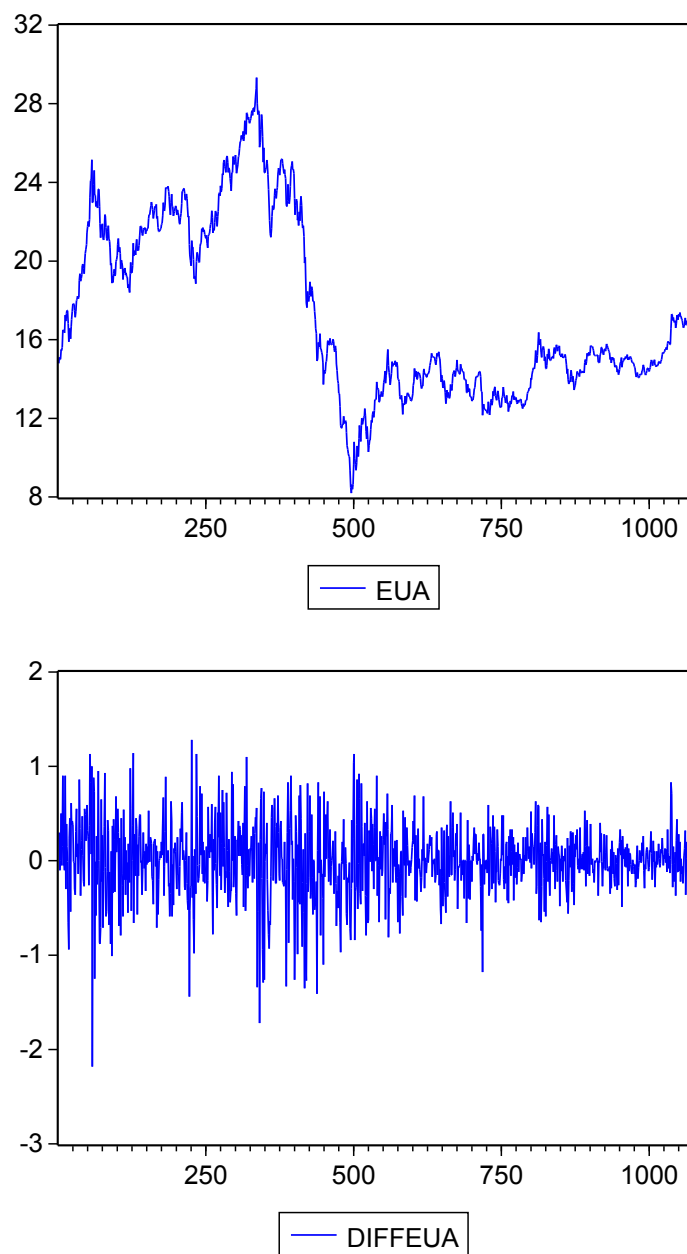
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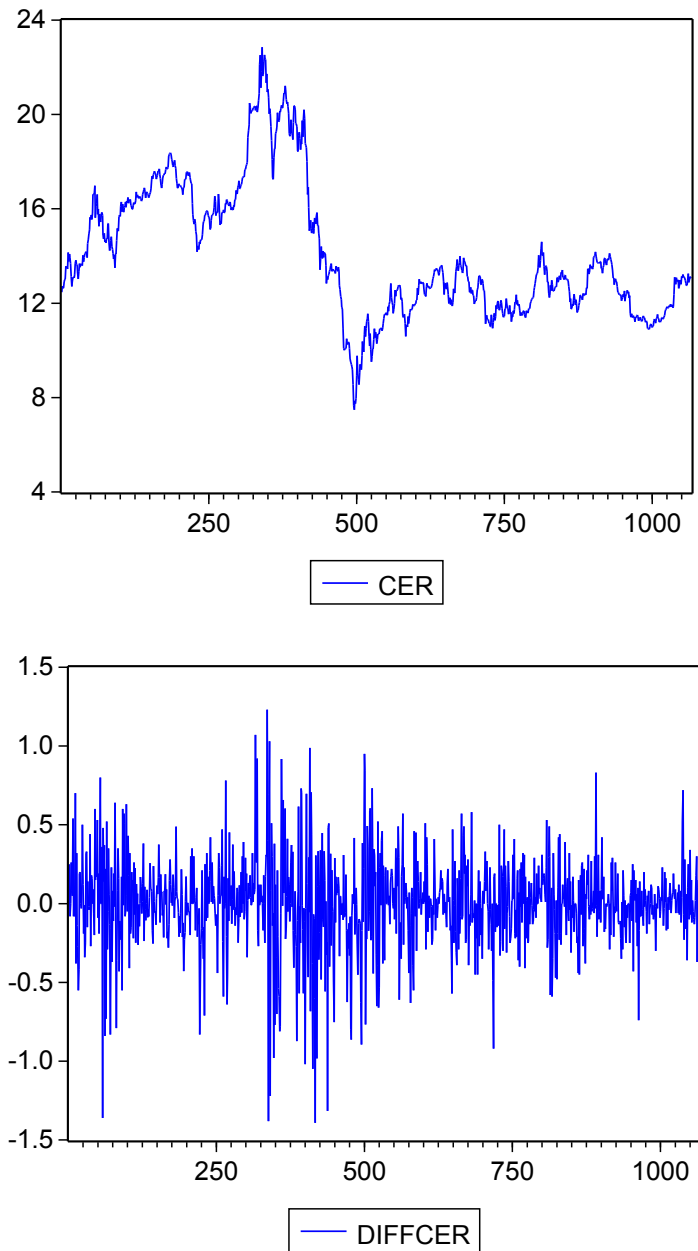
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Figure 1: EUA Futures Price (top) and logreturn (bottom) forms from March 2007 to April 2011



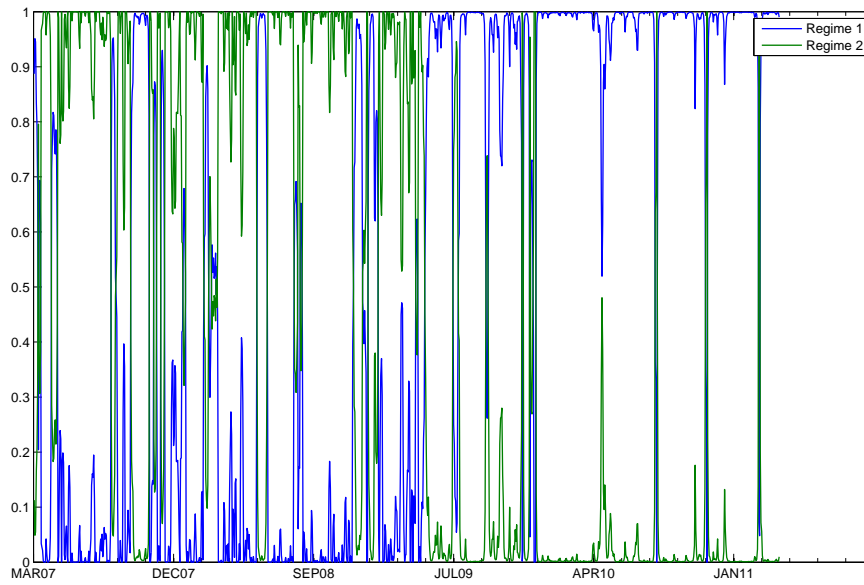
Note: The source of the data is ECX.

Figure 2: CER Futures Price in raw (top) and logreturn (bottom) forms from March 2007 to April 2011



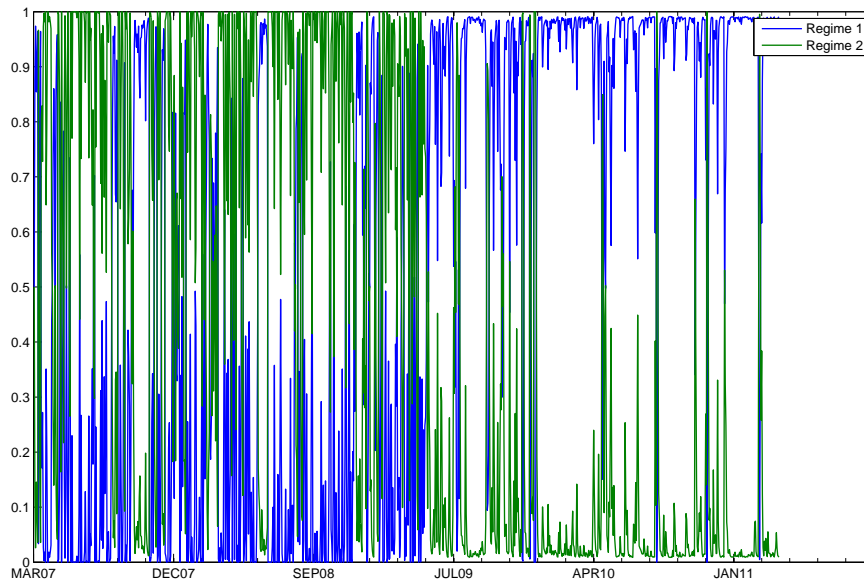
Note: The source of the data is ECX.

Figure 3: Smoothed transition probabilities estimated from the two-regime Markov-switching VAR for *EUAFUTRET* and *CERFUTRET*



Note: Regime 1 is 'expansion'. Regime 2 is 'contraction'.

Figure 4: Regime transition probabilities estimated from the two-regime Markov-switching VAR for *EUAFUTRET* and *CERFUTRET*



Note: Regime 1 is 'expansion'. Regime 2 is 'contraction'.

Table 1: Descriptive statistics for the EUA ECX futures price

	<i>EUAFUT</i>	<i>EUAFUTRET</i>
Mean	17.3523	0.0019
Median	15.3800	0.0001
Maximum	29.3300	1.2800
Minimum	8.2000	-2.1800
Std. Dev.	4.4400	0.3902
Skewness	0.5834	-0.4425
Kurtosis	2.2041	5.2558
JB	88.6199	260.5869
Prob. JB	0.0001	0.0001
Observations	1066	1065

Note: *EUAFUT* stands for the EUA Futures Price, and *EUAFUTRET* for the EUA Futures Price in Logreturn form. Std. Dev. is the standard deviation. JB stands for the Jarque Bera test.

Table 2: Descriptive statistics for the CER ECX futures price

	<i>CERFUT</i>	<i>CERFUTRET</i>
Mean	14.0934	0.0005
Median	13.3350	0.0001
Maximum	22.8500	1.2300
Minimum	7.4846	-1.3916
Std. Dev.	2.8055	0.2946
Skewness	0.7660	-0.4670
Kurtosis	3.0691	6.2029
JB	104.4680	493.9578
Prob. JB	0.0001	0.0001
Observations	1066	1065

Note: *CERFUT* stands for the EUA Futures Price, and *CERFUTRET* for the EUA Futures Price in Logreturn form. Std. Dev. is the standard deviation. JB stands for the Jarque Bera test.

Table 3: Estimation results of the two-regime Markov-switching VAR for *EUAFUTRET* and *CERFUTRET*

Log-likelihood	248.22	
μ (Regime 1)	0.0021*** (0.0001)	
μ (Regime 2)	-0.0029*** (0.0001)	
Equation for <i>EUAFUTRET</i>	<i>EUAFUTRET</i>	<i>CERFUTRET</i>
ϕ_1 (Regime 1)	-0.1088 (0.0672)	0.1211** (0.0528)
ϕ_1 (Regime 2)	0.0895 (0.0510)	0.1104 (0.0790)
ϕ_2 (Regime 1)	0.0994 (0.0551)	-0.2105** (0.1149)
ϕ_2 (Regime 2)	-0.1383* (0.0743)	0.1116 (0.0857)
Equation for <i>CERFUTRET</i>	<i>EUAFUTRET</i>	<i>CERFUTRET</i>
ϕ_1 (Regime 1)	-0.0869 (0.0737)	0.1079 (0.0758)
ϕ_1 (Regime 2)	0.0661*** (0.0265)	0.0835** (0.0484)
ϕ_2 (Regime 1)	0.0704** (0.0340)	-0.1230 (0.0963)
ϕ_2 (Regime 2)	-0.0602*** (0.0274)	-0.0838*** (0.0335)
Standard error (Regime 1)	0.0010	
Standard error (Regime 2)	0.0007	
Transition Probabilities Matrix	Regime 1	Regime 2
Regime 1	0.9500*** (0.0300)	0.0700*** (0.0200)
Regime 2	0.0500*** (0.0100)	0.9300*** (0.0100)
Regime Properties	Prob.	Duration
Regime 1	59.37	19.05
Regime 2	40.63	14.05

Note: *EUAFUTRET* stands for the EUA Futures Price in Logreturn form. *CERFUTRET* stands for the CER Futures Price in Logreturn form. Standard errors are in parentheses. ***, **, * denote respectively statistical significance at the 1%, 5% and 10% levels.

Table 4: Robustness checks of the two-regime Markov-switching VAR for *EUAFUTRET* and *CERFUTRET*

Markov-switching VAR		
LR Statistic	26.758	
<i>p</i> -value	0.001	
Symmetry test	2.606	
<i>p</i> -value	0.021	
RCM 2-State	30.4526	
Distributional Characteristics	<i>EUAFUTRET</i>	<i>CERFUTRET</i>
Mean	0.0006	0.0005
Median	0.0004	0.0002
Maximum	1.2120	1.1079
Minimum	-2.2942	-1.1096
Std. Dev.	0.3459	0.2226
Skewness	-0.4860	-0.4004
Kurtosis	6.3651	5.4188

Note: Distributional characteristics are given for the Markov-switching processes implied by the estimates in Table 3. *EUAFUTRET* stands for the EUA Futures Price in Logreturn form. *CERFUTRET* stands for the CER Futures Price in Logreturn form.