Optimal hedging in carbon emission markets using Markov regime switching models

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Abstract

This paper proposes a Markov regime switching framework for modeling carbon emission (CO_2) allowances that combines a regime switching behavior and disequilibrium adjustments in the mean process, along with a state-dependent dynamic volatility process. We find that all regime switching based hedging strategies significantly outperform single regime hedging strategies (both in-sample and out-of-sample), with the newly proposed framework providing the greatest variance reduction and the best hedging performance. Our results indicate that risk managers using state-dependent hedge ratios to manage portfolio risks in carbon emission markets will achieve superior hedging returns.

JEL Classification: G13, G32, Q47

Key Words: Carbon emission markets, Dynamic hedging, Markov switching models, Dynamic conditional correlation

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1. Introduction

Launched in 2005, the European Union emission trading scheme (EU ETS) is a "cap-and-trade" system[1] aiming at reducing emissions of carbon dioxide and other greenhouse gases (GHG) efficiently and economically. Since inception, the European carbon emission markets under the EU ETS have experienced rapid ongoing development and have attracted considerable attention from policy makers and investors. The total value of European Union allowance (EUA) transactions traded under the EU ETS rose to €106 billion in 2011, with growth rate considerably faster than in other financial markets during the 2008-09 global financial crisis (World Bank, 2012).

Given the novel features and rapid growth of the carbon emission market, a large number of studies in the literature focus on the pricing of carbon emission allowances and their derivatives (Benz and Trück, 2009; Daskalakis, Psychoyios and Markellos, 2009; Li, Chen and Lin, 2015; among others) and modeling the relationship between carbon spot and futures prices (Uhrig-Homburg and Wagner, 2009; Chevallier, 2010; Joyeux and Milunovich, 2010; Rittler, 2012; Philip and Shi, 2015; among others).[2] However, little attention has been drawn to risk management, especially optimal hedging in the carbon emission markets. One exception is the recent attempt by Fan, Roca and Akimov (2014), who study hedging performance in the European carbon markets and suggest that the use of static hedge ratios from the simple ordinary least squares provide the greatest variance reduction in most cases. This can be explained in light of Lien (2008), who identifies certain theoretical conditions for dominance of the ordinary least squares hedging strategy over dynamic hedging approaches. However, the inferior performance of dynamic hedge ratios in Fan, Roca and

[1] Under this system, central authorities set up a standard or "cap" on the total amount of greenhouse gases that a country or region is allowed to emit within a year. The authorities then allocate the allowance of emission units, which is the right to emit a certain amount of greenhouse gases. Operating firms' GHG emissions should not exceed the allocated allowance represented by their in-hand allowances; otherwise they must deliver the missing carbon allowances in the next year and also pay a heavy penalty. GHG emissions that are not covered by the surrendered carbon allowances incur a fine of €40 per CO_2 ton in Phase I and €100 per CO_2 ton in Phase II. In addition, the uncovered carbon allowances should also be surrendered in the next compliance year. As a consequence, the total amount of emissions are controlled and kept under a target level. If an operating firm emits more than its allocated allowance, it can buy emission allowances from other operating firms that possess unused emission allowances. According to the Coase theorem (Coase, 1937, 1960), under the assumption of zero transaction cost, and if the authorities allocate and protect the rights of allowance holders very effectively, the "cap-and-trade" system can completely solve the externalities problem of market failure. For analysis of the impact of the European Union emission trading scheme on low-carbon technological change, see Calel and Dechezleprêtre (2016).

[2] Hintermann, Peterson and Rickels (2016) present a good review of the literature on allowance price dynamics and price determination.

Akimov (2014) may be attributed to the incorrectly specified underlying data generating process. More specifically, recent studies such as Benz and Trück (2009) model the price dynamics of CO_2 emission allowances in the first phase of EU ETS using various time series specifications and find that the Markov regime switching framework outperforms other (AR and GARCH) specifications, both in terms of in-sample fit as well as out-of-sample forecasting. In addition, Chevallier (2011a, 2011b) documents significant gains in using Markov regime switching vector autoregressive models (over single regime vector autoregressive models) to explain the relationship between carbon allowance prices and macroeconomic variables.[3]

This paper is the first to investigate the hedging performance of state-dependent hedge ratios in carbon emission markets. Additionally, it contributes to the literature by proposing a new framework to model the relationship between carbon spot and futures markets that incorporates the concepts of regime switching, disequilibrium adjustment and volatility clustering. This method considers Markov regime switching (MRS) behavior and the long-run relationship of spot and futures prices (LR) in the mean, and a state-dependent dynamics volatility process, which is modeled by Engle's (2002) dynamic conditional correlation (DCC) process. We refer to this model as MRS-LR-DCC. Our approach differs from Lee and Yoder's (2007b) MRS-TVC-GARCH model, whereby we allow the disequilibrium adjustment coefficients to be state-dependent.[4]

Our framework is motivated by the fact that since spot and futures prices are cointegrated, incorporating adjustments to their long-run relationship into the regime switching framework will capture changes in the speed of equilibrium adjustments across different regimes. Additionally, the regime switching specifications are able to accurately capture the various economic characteristics underlying the price dynamics of carbon emission allowances. For example, the demand and supply of carbon allowances, which determine the carbon allowance prices, fluctuate according to the regulatory changes, production levels, and seasonal patterns, among other factors. Such fluctuations can be modeled by allowing a systematic switching between high variance (unstable) and low

[3] See also Li, Chen and Lin (2015), who suggest a Markov regime switching jump diffusion model to price carbon spot and derivatives.
[4] Another difference between our model and the MRS-TVC-GARCH model is that we use Engle's (2002) DCC approach to model the condition correlations, while Lee and Yoder (2007b) employ Tse and Tsui's (2002) approach. The difference between the two methods is in the way we standardize the residuals in the conditional correlations equation.

variance (stable) states. Here, the unquantifiable and unobservable regulatory and sociological factors affecting carbon allowance prices are captured by the unobservable state variables that govern the various regimes. Further, carbon allowance prices are shown to exhibit price jumps, spikes and high volatility (Benz and Trück, 2009; Daskalakis, Psychoyios and Markellos, 2009). Regime switching specifications can model such data generating properties by allowing for several successive price jumps and extreme returns in the data generating process, which is important for risk management.

We evaluate the hedging effectiveness of the MRS-LR-DCC framework for the EU ETS CO_2 emissions market against the optimal hedge ratios generated from a variety of model specifications. We compare the in-sample as well as out-of-sample performances of these strategies, by employing both symmetric and asymmetric risk measures evaluating variance reduction, increase in utility, and reduction on Value at Risk (VaR). The significance of these tests is assessed using White's (2000) Reality Check (RC) test. Moreover, we separately examine the hedging effectiveness of the various strategies for short and long hedgers in carbon markets. The main findings of this paper are summarized as follows. We observe that all the class of Markov regime switching approaches considered substantially outperform alternative strategies for all the performance measures employed, including portfolio variance reduction, utility maximization and VaR exposure minimization, and for both in-sample and out-of-sample analyses. Particularly, within the class of regime switching models, the MRS-LR-DCC model achieves the greatest, and significant, variance improvement compared to competing strategies, indicated by the results of the RC test. In addition, we find that the MRS-LR model constantly outperforms the MRS model in both in-sample and out-of-sample analyses, which supports the argument that the hedging performance can be improved by incorporating the long-run relationship between spot and futures prices. Furthermore, the overall results for the hedging effectiveness of different hedge positions using asymmetric risk measures are mostly in line with those using symmetric metrics; i.e., the class of Markov regime switching approaches outperforms alternative strategies. This implies that no matter what position market participants hold, there is benefit from using state-dependent hedge ratios.

The remainder of the paper is organized as follows. Section 2 presents the MRS-LR-DCC model specification and demonstrates the minimum-variance hedge ratio methodology. Section 3 outlines the data and presents the preliminary descriptive analysis. Section 4 discusses the estimation results from the various hedging models, including the MRS-LR-DCC model. The model hedging effectiveness is evaluated in Section 5, while Section 6 further analyzes the hedging performance by considering the asymmetric risk measure of semi-variance and studies the asymmetric profiles of investors by separately considering the different hedging positions (long hedges and short hedges). Finally, Section 7 summarizes the findings and concludes.

2. The Markov regime switching model

In this section, we introduce a Markov regime switching model (denoted as the MRS-LR-DCC model), where both conditional mean and conditional variance processes are dependent on the volatility of the regime. We consider a two-regime framework defined by high and low variance states. Further, in this model the long-run relationship between spot and futures carbon prices is incorporated in the return process and the coefficient of the long-run relationship is allowed to be state-dependent. Lien and Yang (2008) argue that the lagged basis can help to determine the movement of spot and futures prices and facilitate the mean-reverting process, and therefore can serve as the proxy for the long-run relationship. Kroner and Sultan (1993) and Lai and Sheu (2010), among others, also use the lagged basis as the proxy for the long-run relationship. Therefore, we use the lagged basis to measure the long-run relationship of spot and future prices in this paper. The conditional means of spot and futures returns of the MRS-LR-DCC model are specified as

$$\Delta S_t = \mu_{s,m} z_{t-1} + e_{s,m,t} \tag{1}$$

$$\Delta F_t = \mu_{f,m} z_{t-1} + e_{f,m,t} \tag{2}$$

$$\mathbf{e}_{m,t} = \begin{pmatrix} e_{s,m,t} \\ e_{f,m,t} \end{pmatrix} \Big| \Omega_{t-1} \sim IN(0, \mathbf{H}_{m,t}) \tag{3}$$

where ΔS_t and ΔF_t are respectively spot and futures returns at time t; z_t is the spot-futures basis at time t, which serves as the long-run relationship. The basis is calculated as the logarithmic difference of spot and futures prices multiplied by 100. $\boldsymbol{e}_{m,t}$ is a vector of state-dependent Gaussian write noise processes with a time-varying covariance matrix of $\mathbf{H}_{m,,t}$ at time t. The parameters of the long-run relationship and residuals in the MRS-LR-DCC model depend on the market regime at time t. The unobservable state variables m={1, 2} are assumed to follow a first order, two-state Markov process with the following transition probability matrix:

$$\hat{\mathbf{P}} = \begin{pmatrix} \Pr(m_t = 1 \mid m_{t-1} = 1) = P_{11} & \Pr(m_t = 1 \mid m_{t-1} = 2) = P_{21} \\ \Pr(m_t = 2 \mid m_{t-1} = 1) = P_{12} & \Pr(m_t = 2 \mid m_{t-1} = 2) = P_{22} \end{pmatrix} = \begin{pmatrix} 1 - P_{12} & P_{21} \\ P_{12} & 1 - P_{21} \end{pmatrix} \tag{4}$$

where P_{ij} provides the probability that state i will be followed by state j. The transition probabilities above are presumed to be constant between consecutive periods, and are assumed to follow a logistic distribution:

$$P_{12,t} = \frac{1}{1 + \exp(\phi_1)}; P_{21,t} = \frac{1}{1 + \exp(\phi_2)} \tag{5}$$

where ϕ_1 and ϕ_2 are unconstrained constant terms that are estimated along with other unknown parameters through maximum likelihood estimation.

The conditional variances of spot and futures returns are modeled as GARCH (1,1) processes of Bollerslev (1986).[5] The time-varying, state-dependent and positive definite conditional covariance matrix, $\mathbf{H}_{m,t}$, is specified as

$$\mathbf{H}_{m,t} = \begin{pmatrix} h^2_{s,m,t} & h_{sf,m,t} \\ h_{sf,m,t} & h^2_{f,m,t} \end{pmatrix} = \begin{pmatrix} h_{s,m,t} & 0 \\ 0 & h_{f,m,t} \end{pmatrix} \begin{pmatrix} 1 & \rho_{m,t} \\ \rho_{m,t} & 1 \end{pmatrix} \begin{pmatrix} h_{s,m,t} & 0 \\ 0 & h_{f,m,t} \end{pmatrix} \tag{6}$$

where $\rho_{m,t}$ is state-dependent conditional correlation between spot and futures returns at time t in state m= {1, 2} and $h^2_{s,m,t}$ and $h^2_{f,m,t}$ are the state-dependent conditional variances at time t in state m for spot and futures returns, respectively. Specifically, the conditional variances and conditional correlation in Engle's (2002) dynamic conditional correlation (DCC) GARCH framework are shown as

$$h^2_{s,m,t} = \gamma_{s,m} + \alpha_{s,m} e^2_{s,t-1} + \beta_{s,m} h^2_{s,t-1} \tag{7}$$

$$h^2_{f,m,t} = \gamma_{f,m} + \alpha_{f,m} e^2_{f,t-1} + \beta_{f,m} h^2_{f,t-1} \tag{8}$$

$$\rho_{m,t} = (1 - \theta_{1,m} - \theta_{2,m})\rho + \theta_{1,m} \boldsymbol{\eta}_{t-1} \boldsymbol{\eta}'_{t-1} + \theta_{2,m} \rho_{m,t-1} \tag{9}$$

[5] In some cases involving the out-of-sample analysis, we cannot get convergence results by using standard GARCH (1,1) specification. In order to get convergence results, the asymmetric power ARCH (APARCH) model of Ding, Granger and Engle (1993) is adopted in these cases.

where $\theta_{1,m}$ and $\theta_{2,m}$ are the DCC parameters, ρ is the initial value of the conditional correlation, and $\boldsymbol{\eta}_t$ is a matrix for the standardized residuals. At this stage, all the parameters in the system are state-dependent.

However, since both conditional variances and conditional correlations are based on all the past information recursively, the basic form of GARCH models with state-dependent coefficients is intractable (see, for example, Hamilton and Susmel, 1994; Cai, 1994). Gray (1996) solves the path-dependency problem in the univariate GARCH framework by formulating the conditional variance process as the conditional expectation of the variance. Following Gray (1996), Lee and Yoder (2007a) extend the collapsing method for conditional residuals, conditional variances and conditional covariance in the bivariate framework. We follow Lee and Yoder's (2007a) method to recombine the conditional variance and residuals of the spot and futures returns. The technical details are provided in Appendix A.

Using the MRS-LR-DCC framework outlined above, we estimate the optimal hedge ratios (g_t) as

$$g_t = \frac{Cov(\Delta S_t, \Delta F_t)}{Var(\Delta F_t)} = \frac{h_{sf,t}}{h_{f,t}^2} = \rho_t \frac{h_{s,t}}{h_{f,t}} . \tag{10}$$

We compare the hedging performance of the MRS-LR-DCC model against alternative regime switching specifications including the MRS model given by

$$\Delta S_t = \gamma_{0,m} + \gamma_{1,m} \Delta F_t + e_{m,t} ;\ e_{m,t} \sim iid(0, \sigma_{m,t}^2) , \tag{11}$$

and the MRS model with the long-run relationship specification (MRS-LR) given by

$$\Delta S_t = \gamma_{0,m} + \gamma_{1,m} \Delta F_t + \gamma_{2,m} z_{t-1} + e_{m,t} ;\ e_{m,t} \sim iid(0, \sigma_{m,t}^2) , \tag{12}$$

where the transition probabilities of these models follow a logistic distribution described in Equation (5). The minimum variance hedge ratios for the various states of the market are derived from the coefficients $\gamma_{1,1}$ and $\gamma_{1,2}$. More specifically, the optimal hedge ratio at a given time t is determined as the weighted average of the minimum variance hedge ratios in each state, according to the probability of being in each state, which is shown as

$$g_t = \pi_{1,t} \gamma_{1,1} + (1 - \pi_{1,t}) \gamma_{1,2} \tag{13}$$

3. Data and preliminary diagnostics

The dataset comprises daily closing (settlement) spot and futures prices of EUAs from the recent EU ETS Phase II period, spanning from March 03, 2008 to November 30, 2012. We do not include the data from the EU ETS Phase I period since the return dynamics of the EUAs are substantially different from the other phases due to regulatory and trading mechanism changes. Additionally, due to inter-phase banking restrictions, the spot prices were close to zero at the end of Phase I, i.e. the second half of 2007 (Chevellier, 2011a). Hence, we exclude the return dynamics during the Phase I period for implementing hedging models.

The spot prices of the carbon allowances are obtained from BlueNext Exchange and the carbon futures prices are from the Intercontinental Exchange (ICE). In order to construct a continuous series of carbon futures prices, similar to previous work, it is assumed that hedgers switch over futures contracts from the contact nearest to maturity to that second nearest to maturity on the first business day after the expiry date of the contract nearest to maturity, for all available traded months.[6]

[Insert Table 1 here]

The summary statistics, unit root tests and cointegration tests of the carbon spot and futures price levels and (logarithmic) returns series for both in-sample and out-of-sample periods are shown in Table 1. It is found that the mean prices of spot and futures in the out-of-sample period are significantly lower than those in the in-sample period, while the mean returns of spot and futures in the out-of-sample period are higher and closer to zero than those in the in-sample period. The standard deviation, skewness and kurtosis for price levels and returns and for spot and futures also show significant differences between the in-sample and out-of-sample periods. This indicates that the distributions of prices and returns are different in the two periods, which may cause the out-of-sample hedging based forecasting to be less effective than the in-sample one.[7] The Jarque and Bera (1980) statistics show that all the series considered significantly depart from normal distribution. The results of Ljung and Box (LB)'s (1978) Q tests for the 12th lags of autocorrelation indicate that spot and futures prices

[6] The EUA futures contracts listed on ICE are on a quarterly expiry cycle; i.e., contracts mature in March, June, September and December each year. The maturity date is the last Monday of the contract maturity month.

[7] This may be because the out-of-sample period is approaching the end of the second phase of EU ETS and some carbon emission allowances cannot be used the next phase due to the interphase banking restrictions.

are serially correlated while there is no evidence of serial correlation in the spot and futures return series, for both in-sample and out-of-sample periods. Furthermore, the LB tests on the squared series for Engle's (1982) ARCH effect suggest the presence of volatility clustering in all series except for the out-of-sample spot returns. The results of Phillips and Perron's (1988) unit root tests indicate that all the price series are non-stationary while all the return series are stationary. Finally, the cointegration test of Johansen (1988) shows that the spot and futures prices are cointegrated with one cointegration vector. The normalized cointegration vector is very close to (1 -1 0), indicating that the spot-futures basis can serve as the long-run relationship.

[Insert Figure 1 here]

The time series of spot-futures basis (in percentage) is plotted in Figure 1. It is shown that the basis of carbon emission allowances is below zero in most cases, indicating that the carbon markets is normally in backwardation. Moreover, the basis generally lies in the range between -3% and 1%, which is less volatile than that in the WTI crude oil markets shown in Alizadeh, Nomikos and Pouliasis (2008).

4. Estimation Results

This section presents the in-sample results of the Markov regime switching model frameworks introduced in Section 2.[8] To remain parsimonious, we allow all the regime switching models to have two possible states/regimes: a high variance state and a low variance state. Table 2 displays the estimation results of MRS and MRS-LR models.

[Insert Table 2 here]

Several interesting points are shown in Table 2. Firstly, it can be observed that the adjusted R^2 in the MRS-LR model is higher than that of the MRS model, indicating a better overall fit for the MRS-LR model for the dynamics of the carbon spot-futures relationship. This supports the view that the lagged basis, serving as the long-run relationship, can provide additional information for modeling the relationship between carbon spot and futures returns. Secondly, the minimum variance hedge ratio ($\gamma_{1,m}$) of the MRS-LR model is slightly higher

[8] We also estimate various other model specifications including the constant OLS and the VECM model. For brevity, the estimation results for these models are not reported and are available upon request.

than that of the MRS model in state 1, but lower than that of the MRS model in state 2. Since $\gamma_{1,1}$ and $\gamma_{1,2}$ can be considered as the upper and lower boundaries of the optimal hedge ratios, the MRS-LR model provides a broader window of optimal hedge ratios than the MRS model. Thus the MRS-LR model is better able to capture the changing market conditions. Thirdly, the volatilities (σ_m) and inter-state transitional probabilities (P_{12} and P_{21}) are lower in the MRS-LR model than the MRS model, suggesting that the MRS-LR is more stable.

From the volatility estimates for each regime, it can be observed that state 1 is the low variance state, while state 2 is the high variance state. It can be further noted that the minimum variance hedge ratio in the low variance state is higher and closer to the naïve hedge (with g_t = 1) than in the high variance state. This may be because when variance is low, the spot-futures relationship is more stable and closer to the long-run equilibrium of (1 -1 0), and therefore the hedge ratio is near 1. The high variance state captures the price jumps so that the optimal hedge ratio deviates from 1. Further, the transitional probability from the low variance state to the high variance state (P_{12}) is lower than that of the inverse (P_{21}), indicating that the low variance state is more stable and has a longer duration. More specifically, the inter-state transition probabilities of the MRS model are P_{12}=0.0517 and P_{21}=0.1377, suggesting that the average expected durations (AED) of being in state 1 and state 2 are around 19 (=1/0.0517) days and about 7 (=1/0.1377) days, respectively.[9] For the residual diagnostics of the models, we observe that the residuals are not normally distributed and have significant autocorrelation and heteroskedasticity. Hence, we enhance the MRS-LR framework by modeling the residual process with the dynamic conditional correlation model of Engle (2002). The full specification of this model is outlined in Section 2 and referred to as the MRS-LR-DCC model.

[Insert Table 3 here]

Table 3 reports the results for the MRS-LR-DCC model, along with results from the standard (single-regime) DCC-GARCH specification of Engle (2002) for comparison. For the conditional mean equation of the MRS-LR-DCC model, the parameters of lagged basis, $\mu_{s,m}$ and $\mu_{f,m}$, govern the adjustment speed of spot and futures prices to their long-run equilibrium. In the low variance state, the speed of adjustment is negative and significant for the spot

[9] Hamilton (1989) shows that the average expected duration in the first state is calculated as $AED_1 = \sum_{i=1}^{\infty} iP_{11}^{i-1}(1-P_{11}) = (1-P_{11})^{-1} = P_{12}^{-1}$.

equation, while it is positive but insignificant for the futures equation. This implies that spot prices significantly react to converge to the long-run equilibrium relationship. More specifically, if there is a positive deviation from the equilibrium at time t-1 (i.e. $S_{t-1} > F_{t-1}$), the spot price at time t will decrease as a response to the deviation, while the response of the futures price at time t will be insignificant. As a consequence, the long-run relationship between spot and futures price is restored. In the high variance state, the speed of adjustment is still negative and significant for the spot equation, and insignificant for the futures equation. However, the magnitude of the adjustment speed increases dramatically compared to the low variance state. This suggests that when there is a large deviation from the equilibrium (i.e. in the high variance state), the response of the spot price in the next period will be more significant in order to re-establish the long-run relationship. When we compare these results to those of the single-regime DCC-GARCH model, we observe that the coefficients of the lagged basis for both spot and futures equations are negative and significant, and thereby qualitatively different from both low and high state results of the MRS-LR-DCC model. Overall, the results imply that the mean equation dynamics underlying the carbon spot and futures prices are different across the high and low states of the markets. More specifically, there are regime shifts in the mean-reverting process and the responses to shocks deviating from the long-run equilibrium depend on the volatility of the states.

Next, we focus on Table 3 results for the conditional variance and conditional correlation equations. We observe that the variance equations' intercept term as well as the ARCH and GARCH parameters in the low variance state are distinct from those in the high variance state. This suggests that the conditional variance process in the carbon emission markets is also state-dependent, evidence that has not been documented in the literature. When we consider the volatility persistence in the spot and futures markets, we find higher volatility persistence in the high variance states as compared to that in the low variance states. Comparing these results to the single-regime DCC-GARCH model, we find that the degree of volatility persistence captured by the single regime volatility model is lower than the degree of volatility persistence observed in both the high and low variance states of the MRS-LR-DCC model. For the regime transition probabilities of the MRS-LR-DCC model, we see that the transitional probability from the low variance state to the high variance state (P_{12}=0.0781) is significantly smaller than that of the inverse (P_{21}=0.3888), showing that the low variance state has a longer average expected duration (AED=1/0.0781≈13 days) than the high variance state (AED=1/0.3888≈3 days) and is more steady. As compared to the regime transition probabilities of the MRS-LR model reported in Table 2, we observe that the average expected duration in any particular regime has decreased. Finally, the residual diagnostic tests of the DCC-GARCH and MRS-LR-DCC models are shown at the bottom of Table 3. The results of LB (12) and LB^2 (12) tests indicate that the residuals from the two models dramatically improve over the previous model specifications (MRS and MRS-LR) reported in Table 2.

[Insert Figure 2 here]

The estimated smooth regime probabilities of the MRS-LR-DCC model are reported in Figure 2. We obtain the smooth regime probabilities as the estimated conditional probabilities of being in a particular state at time *t*, given the entire sample of observations up to the end of the sample period. For the details of estimated regime probabilities, see Hamilton (1994). We observe that the high variance state is generally short-lived, while the low variance state prevails for longer periods. The high variance state is much more evident during the initial parts of the sample, which corresponds to the regulatory changes due to the introduction of the EU ETS Phase II Scheme.

5. Optimal hedge ratios and hedging performance

From the estimated MRS-LR-DCC model, we obtain the time-varying conditional variances and the conditional correlations. The optimal hedge ratios are then calculated by using Equation (10). For comparison, we calculate the optimal hedge ratios from the naïve model (i.e. a naïve hedge ratio equal to unity), the constant OLS model, and the vector error correction model (VECM) of Engle and Granger (1987), as well as time-varying hedge ratios generated from the DCC-GARCH, MRS and MRS-LR models. In Figure 3, Panel A compares the hedge ratios from the naïve, OLS, DCC-GARCH and MRS-LR-DCC models for the in-sample period, while the comparison of the in-sample hedge ratios generated from the class of Markov regime switching models (MRS and MRS-LR-DCC models) are displayed in Panel B.[10] It can be observed that the MRS-LR-DCC hedge ratios are the most volatile among all the competing hedging strategies, implying that the hedged portfolio has to be rebalanced frequently.

[Insert Figure 3 here]

[10] The hedge ratios from the MRS-LR model are very close to those from the MRS model and hence are not displayed in Figure 3.

[Insert Table 4 here]

To evaluate the hedging performance of these competing strategies, the hedged portfolios are constructed every trading day and the returns (r_t) are given by

$$r_t = \Delta S_t - g_t \Delta F_t \tag{14}$$

where g_t denotes the optimal hedge ratios from each model. A smaller variance of the hedged portfolio ($Var(r_t)$) indicates a better hedging strategy. The in-sample hedging effectiveness of Markov regime switching models and the alternative hedging model strategies is displayed in Panel A of Table 4. The in-sample period spans from March 03, 2008 to May 31, 2012 (1109 observations). It is shown that the hedged portfolio generated from the MRS-LR-DCC model has the lowest variance among all the hedging strategies, followed by the MRS-LR and MRS models. This indicates that the class of Markov regime switching models outperforms the other constant and time-varying hedging models in terms of in-sample variance reduction. In particular, the MRS-LR-DCC provides an impressive in-sample variance improvement over the other models of around 14.7% to 22.9%. We observe that the percentage variance improvements of Markov regime switching hedging models for carbon emission markets are significantly greater than the improvements recorded for other markets, such as in the case of corn and nickel markets (Lee and Yoder, 2007a), oil markets (Alizadeh, Nomikos and Pouliasis, 2008), and tanker shipping markets (Alizadeh, Huang and Van Dellen, 2015), as well as various stock market indices (Lee and Yoder, 2007b; Salvador and Arago, 2014). Overall, our results suggest that regime switching models accurately capture the time series dynamics in carbon emission markets and are particularly useful for the purpose of hedging.

Nevertheless, the superior performance of the MRS-LR-DCC hedge may be due to the data snooping bias induced by using posterior information (see Sullivan, Timmermann and White, 1999; White, 2000 for details). Hence, we use White's (2000) Reality Check (RC) test to examine the statistical significance of the variance improvement underlying the MRS-LR-DCC hedge relative to the other hedging strategies. Considering variance of the hedged portfolio as the performance measure, let f_k denote the performance measure of the MRS-LR-DCC model relative to the k^{th} benchmark model. When f_k is positive, the MRS-LR-DCC model achieves greater variance reduction than the k^{th} benchmark model. In order to test the statistical significance of the variance reduction, the null hypothesis is that the MRS-LR-

DCC model is not superior to the k^{th} benchmark model in terms of variance reduction, which can be expressed as

$$H_0 : \max_k E(f_k) \leq 0 \, . \tag{15}$$

The RC test statistic is given by

$$T_n^{RC} = \max_k (n^{1/2} \overline{f}_k) \, ,$$

where $\overline{f}_k = \frac{1}{n} \sum_{t=1}^{n} f_{k,t}$ and n is the number of forecasting periods. In order to compute the p-values of the test statistic, we adopt Politis and Romano's (1994) stationary bootstrap methodology, which retains the distributional characteristics of the original data. The method consists of resampling the original data with different block lengths, assuming the block length is following a geometric distribution with a given mean (see Politis and Romano (1994) for the details of stationary bootstrap). The p-value of the RC test is computed by comparing the observed test statistics T_n^{RC} with the quantiles of simulated distribution of test statistics $T_n^{RC^*}$, which is given by

$$T_n^{RC*} = \max_k \left\{ n^{1/2} [\overline{f}_k^*(j) - \overline{f}_k] \right\} , \tag{16}$$

where $\overline{f}_k^*(j)$ denotes the sample mean of relative hedging performance measure computed from the j^{th} simulated sample, for j = 1, 2, …, 1000. The results of the RC tests reported in Table 4 indicate rejection of the null hypothesis for all the competing hedging models. Hence, we find that the variance improvement of the MRS-LR-DCC model is statistically superior to all the alternative hedging strategies considered.

Next, we investigate the potential economic benefits realized from implementing the MRS-LR-DCC model hedging strategies. Hedgers are required to rebalance their hedged portfolios frequently when implementing dynamic hedging strategies. Therefore, transaction costs are not negligible in the hedging performance of various strategies. Kroner and Sultan (1993) and other studies employ the hedger's utility as a measure of hedging performance, which considers the economic benefits of hedging. The utility function of a hedger is given by

$$E_{t-1}U(r_t) = E_{t-1}(r_t) - \lambda Var_{t-1}(r_r)\,, \tag{17}$$

where r_t is the hedged portfolio return at time t and λ is the degree of risk aversion. Following Lee (2010), it is assumed that the expected hedged portfolio return is zero and the degree of risk aversion is 4.[11] From Table 4, we observe that the average daily utility gain from using a MRS-LR-DCC-based hedging strategy is -2.0644 and is the highest realized gain among all the other hedging strategies considered. If we compare the MRS-LR-DCC hedge against the OLS hedge, we see an improvement in the daily average utility for about 0.4788 units, before considering transaction costs. Mizrach and Otsubo (2013) estimate the average transaction cost to be around 0.14% for the EUA contracts in 2009. However, the costs of rebalancing will be even lower, as only a fraction of the portfolio is rebalanced. Hence, using the MRS-LR-DCC hedge can provide an increase of utility for the hedgers in the market, even after considering the relevant transaction costs.

Another measure to assess the hedging effectiveness is the Value at Risk (VaR) used by Cotter and Hanley (2006). A better hedging strategy can provide a reduction in the VaR exposure. Assuming the hedged portfolio return is following a normal distribution, the VaR of the hedged portfolio at confidence level α is shown as

$$VaR = V_0[E(r_t) + z_\alpha \sqrt{Var(r_t)}]\,, \tag{18}$$

where V_0 denotes the initial wealth of the portfolio and z_α represents the α percent quantile of the normal distribution. Assuming a €1 million initial wealth and 95% confidence level, the daily average VaR exposure for the MRS-LR-DCC hedge can be calculated to be -€11,817.5, which is a decrease of €1,299.5, as compared to the daily average VaR exposure of -€13,117.0 for the OLS hedge. Overall, the in-sample results strongly support the use of the Markov regime switching models for hedging carbon emission allowances, as they provide economic benefits, such as an increase in average utility and a decrease in the average VaR exposure, after accounting for the costs of portfolio rebalancing.

Although the in-sample results show the advantages of using Markov regime switching models for hedging carbon emission allowances, risk managers are more concerned about how the models perform out-of-sample. Our out-of-sample period spans from June 01, 2012 to November 30, 2012. Panel B of Table 4 reports the out-of-sample hedge performance

[11] All the mean returns of the hedged portfolios using different hedging strategies in this study are less than 0.00%; thus it is reasonable to assume the expected return is zero.

results for all the hedging strategies considered previously. For the out-of-sample analysis, all the models are estimated recursively and we generate one-step-ahead hedging strategies based on the optimal forecasts of the hedge ratios. We observe that the out-of-sample results provide a consistent picture, similar to the in-sample analysis. That is, the hedging strategies based on the MRS-LR-DCC model provide the greatest variance reduction, followed by the hedging strategies based on the MRS-LR and the MRS models. We find that all the single-regime-based hedges underperform vis-à-vis those based on the Markov regime switching models. The results of the RC test indicate that the MRS-LR-DCC model provides significant out-of-sample variance reduction as compared to the alternative models. The economically significant tests reveal that hedgers gain an incremental average daily utility of 0.958 if they use the MRS-LR-DCC hedge ratios as compared to the OLS-based hedge ratios. Further, hedgers can reduce the average daily VaR exposure by €1,193.3 by implementing the MRS-LR-DCC hedging approach.

To summarize, the above results show that the class of Markov regime switching models considerably outperform competing models in terms of portfolio variance reduction, utility maximization and reducing VaR exposure, both in-sample and out-of-sample. In particular, the MRS-LR-DCC hedges achieve the greatest variance reduction, and the RC test results demonstrate that there are significant variance improvements in using the MRS-LR-DCC hedges over competing hedging strategies. The above findings illustrate the importance of using Markov regime switching models in hedging carbon emission allowances.

6. Hedging performance under conditions of asymmetry

In this section, we investigate the hedging effectiveness of Markov regime switching models in capturing the asymmetries in the return distribution of carbon markets. While traditional performance measures such as variance reduction allocate equal weight to profits and losses, risk managers are generally more concerned about the downside risk (see for example, Adams and Montesi, 1995). Hence, we use the asymmetric risk metric of semi-variance to study the hedging effectiveness in carbon emission markets. Moreover, we study the asymmetric profiles of investors by separately considering the different hedging positions (long hedges and short hedges). This is motivated by the significant differences in hedging performance among short and long hedgers observed by Demirer and Lien (2003) and Cotter and Hanley (2006).

The nature and statistical properties of Markov regime switching models would mean that such models can potentially better capture the non-normalities and the time-varying nature of the higher moments governing the return distribution. Following Cotter and Hanley (2006), we define the negative and positive semi-variance metric as

$$SVar_{(-)} = E\{[\min(0, r_t - R)]^2\}, \tag{19}$$

$$SVar_{(+)} = E\{[\max(0, r_t - R)]^2\}, \tag{20}$$

where R is the target return, which is set as zero in order to distinguish between positive and negative hedged portfolio returns, r. A short hedger is mainly concerned about the negative returns on the hedged portfolio and hence favors a hedging strategy with the lowest negative semi-variance. In contrast, a long hedger is concerned about the positive portfolio returns and seeks a hedge with the minimum positive semi-variance. Thus, the short and long hedgers optimize the associated risk measures over the opposite portions of the hedged portfolio return distribution.

[Insert Table 5 here]

Table 5 reports the in-sample and out-of-sample hedging effectiveness of various hedging strategies for short and long hedgers in carbon markets. The short hedge results are shown in Panel A, while the results of long hedge positions are displayed in Panel B. In addition to the semi-variance metric, we also report other asymmetric measures of hedging performance, including semi-utility and asymmetric VaR exposure, which are estimated using the semi-variance metrics. The 5% quantiles of the normal distribution are used to estimate the asymmetric VaR exposure, assuming that positive and negative returns of the hedged portfolio follow a half normal distribution.

Consistent with previous evidence, the in-sample test results show that the MRS-LR-DCC hedging strategy outperforms alternative strategies by providing the greatest semi-variance reduction, maximum semi-utility and a minimum asymmetric VaR exposure. According to White's (2000) RC test, the semi-variance improvements of the MRS-LR-DCC hedge are statistically significant both for short hedgers and long hedgers. We observe that the MRS-LR-DCC hedge performs considerably better for short hedges (with a semi-variance improvement of 23.7%-29.5%) than long hedges (6.0%-14.5% improvements), implying that the MRS-LR-DCC model is able to capture downside portfolio risks better. For the out-of-sample analysis, we find that the MRS-LR-DCC model still provides best for hedging performance for short hedge positions. The semi-variance improvements of the MRS-LR-DCC model compared to other models are rather remarkable (64.1%-72.0% improvements) and strongly significant (all the p-values of RC=0.00). However, for long hedging positions, the MRS-LR-DCC model is significantly outperformed by the VECM model, which can provide an improvement of more than 6% in semi-variance compared to the MRS-LR-DCC model. We also notice that the other Markov regime switching models do not perform well for long hedgers. These findings imply that Markov regime switching approaches can capture downside risks significantly better than any other hedging models for short hedging positions in carbon emission markets, i.e. when investors have spot carbon emission allowances in-hand and wish to sell carbon futures contracts to hedge the potential losses due to drops of carbon spot prices.

7. Conclusion

This paper examines the hedging effectiveness of state-dependent hedge ratios in the European carbon emission markets. This is motivated by Benz and Trück (2009) and Li, Chen and Lin (2015), who find that the carbon asset prices can be better characterized by regime switching models. This implies that the hedge ratios generated from regime switching models could have superior hedging performance than single regime hedging models. For this reason, this paper proposes a Markov regime switching model (denoted as MRS-LR-DCC) to hedge the market risk in carbon emission markets. In particular, we propose a two-regime model, incorporating the long-run relation between spot and futures prices (measured by lagged basis) in the mean process, with a state-dependent dynamic volatility process.

Using the EU ETS Phase II spot and futures daily prices, we find that all the class of Markov regime switching models considered outperform (both in-sample and out-of-sample) competing hedging strategies in terms of all the hedging performance measures considered, i.e. portfolio variance reduction, utility maximization and VaR exposure minimization. The variance reduction of MRS-LR-DCC for carbon emission markets is significantly greater than the improvements recorded for other markets (see Lee and Yoder, 2007a, b; Alizadeh, Nomikos and Pouliasis, 2008; Salvador and Arago, 2014; Alizadeh, Huang and Van Dellen, 2015). The results of White's (2000) RC test demonstrate that the variance improvements of the MRS-LR-DCC model over competing approaches are statistically significant, both in-sample and out-of-sample. Further, we also find that the MRS-LR model consistently outperforms the MRS model in both in-sample and out-of-sample analysis, which suggests that the lagged basis term, capturing the long-run relationship, provides additional information for hedging in carbon markets.

In addition to using symmetric hedging performance indicators, we investigate the hedging effectiveness of Markov regime switching models in capturing the asymmetries in the return distribution of carbon markets. Using asymmetric risk measures and distinguishing the hedge performance of short and long hedgers, we find a consistent picture in the in-sample analysis, where we find that the MRS-LR-DCC hedge tops all the other hedging strategies considered. In particular, we observe that the semi-variance reduction by using the MRS-LR-DCC hedge for short hedge positions is considerably greater than for long hedge positions. In fact, the Markov regime switching family of models underperform other competing strategies out-of-sample for the long hedge positions. These results suggest that the Markov regime switching models capture the asymmetries of negative returns better than positive returns. Overall, market participants can benefit from using regime switching hedging strategies, no matter what position they hold.

To summarize, the above findings demonstrate the importance of using Markov regime switching models in hedging carbon emission allowances. Financial risk managers who adopt state-dependent hedge ratios will achieve greater variance reduction and better hedging performance. Further research into allowance hedging dynamics could examine the information content that drives the regime switching behavior observed in the carbon market. For instance, the price regimes may be driven by factors such as future macroeconomic uncertainty, future fuel demand variations, among others. Identifying such economic factors will enable us to better interpret the results from these models.

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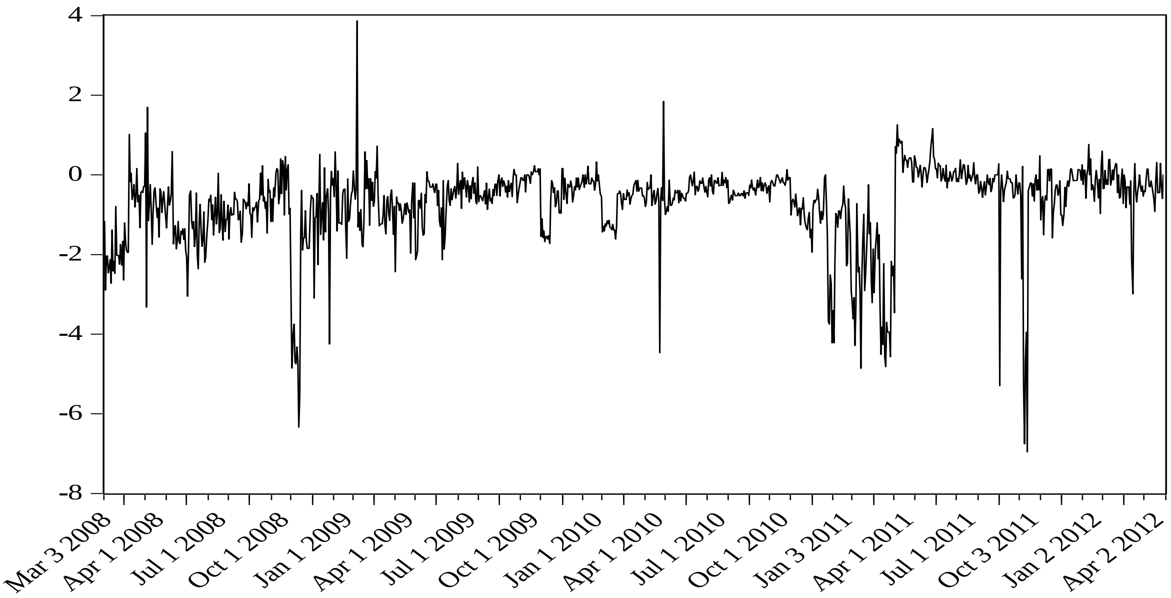
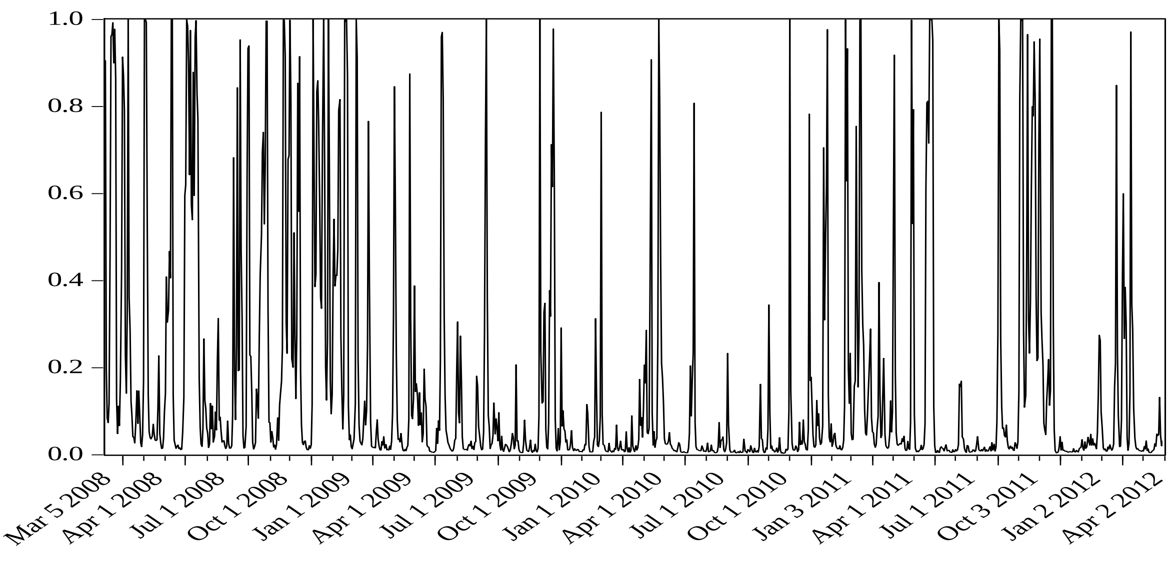
Figure 1: Spot-futures basis for carbon emission allowances



This figure displays the time series of spot-futures basis for carbon emission allowance. Basis is defined as the logarithmic difference of spot and futures prices in percentage form.

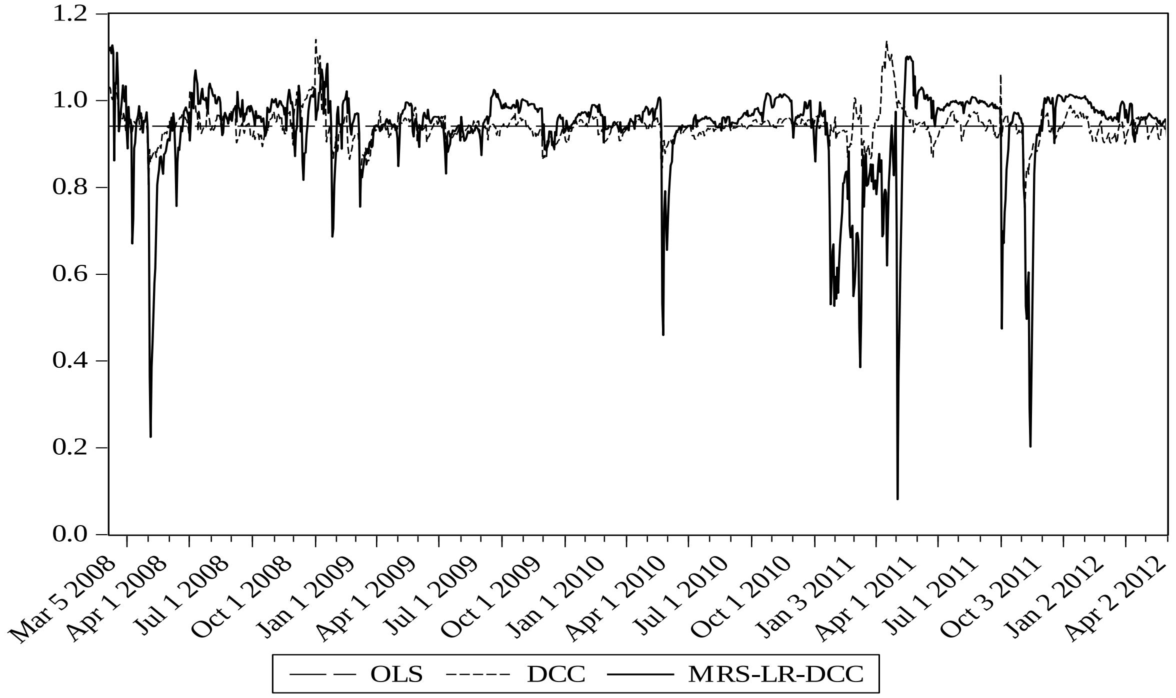
Figure 2: Smooth regime probabilities for carbon emission allowances



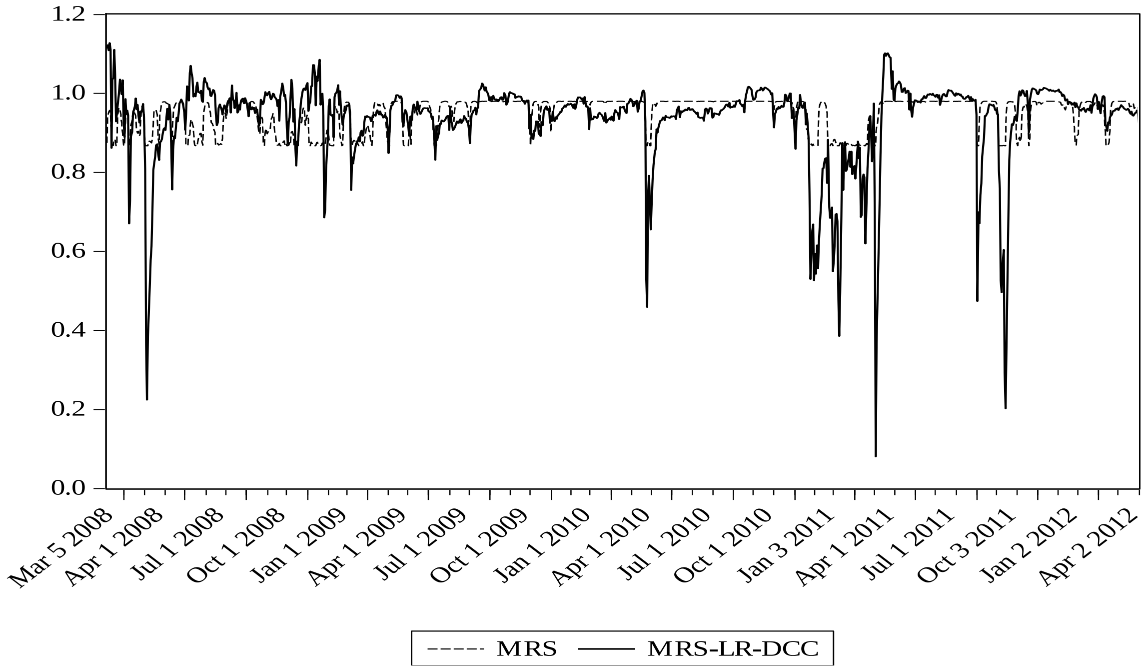
This graph shows the smooth regime probabilities of being in the high variance state generated from the MRS-LR-DCC model for carbon emission allowances.

Figure 3: Alternative hedge ratios for carbon emission allowances

Panel A: Plot of Constant OLS, DCC-GARCH and MRS-LR-DCC hedge ratios



Panel B: Plot of MRS and MRS-LR-DCC hedge ratios



This figure plots the constant OLS hedge ratio and the dynamic hedge ratios of DCC-GARCH, MRS, and MRS-LR-DCC models.

Table 1: Summary statistics, unit root and cointegration tests for spot and futures prices of carbon emission allowances

Panel A: Descriptive statistics

	In-sample				Out-of-sample			
	Spot Prices	Futures Prices	Spot Returns	Futures Returns	Spot Prices	Futures Prices	Spot Returns	Futures Returns
Mean	2.6261	2.6333	-0.1077	-0.1086	2.0068	2.0195	-0.0012	-0.0086
S.D.	0.3364	0.3386	2.6375	2.6707	0.0874	0.0766	3.0608	2.7929
Skewness	-0.241	-0.238	0.103	0.104	-0.637	-0.521	1.053	-0.498
Kurtosis	3.163	3.154	7.858	7.306	2.496	2.488	11.230	4.905
J-B	11.960	11.589	1091.3	858.10	10.244	7.359	393.91	25.218
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.03)	(0.00)	(0.00)
LB(12)	12388	12383	13.211	13.401	421.3	383.4	10.542	9.975
	(0.00)	(0.00)	(0.35)	(0.34)	(0.00)	(0.00)	(0.57)	(0.62)
$LB^2(12)$	12488	12484	221.75	290.90	417.10	381.50	8.327	21.388
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.76)	(0.05)
PP test	-0.525	-0.515	-32.308	-32.330	-2.217	-2.243	-8.967	-9.654
	(0.88)	(0.89)	(0.00)	(0.00)	(0.20)	(0.19)	(0.00)	(0.00)

Panel B: Cointegration tests (in-sample only)

Lag	H_0	λ_{max} test	λ_{trace} test	Normalized CV (1 β_2 β_0)
2	k=0	75.595***	75.344***	(1 -0.9941 -0.0082)
	k≤1	0.251	0.251	

This table provides summary statistics, unit root and cointegration tests for spot and futures prices of carbon emission allowances, for both in-sample and out-of-sample periods. The in-sample period is from March 03, 2008 to May 31, 2012 (1109 observations), whereas the out-of-sample period is from June 01, 2012 to November 30, 2012 (half a year, 131 observations). Spot and futures prices are logarithmic prices of carbon spot and futures. Spot and futures returns are the percentage difference of the logarithmic prices. J-B stands for the Jarque and Bera (1980) test for Normality. LB(12) and $LB^2(12)$ are Ljung and Box's (1978) Q tests for 12th order autocorrelation in the level and squared series, respectively. PP test is Phillips and Perron's (1988) unit root test. Lag is the optimal lag length of the unrestricted VAR model in levels. Optimal lag length is selected based on the Schwarz (1978) Information Criterion (SIC). The null hypothesis of λ_{max} tests and λ_{trace} tests is that the number of cointegration vectors is less than or equal to k, where k is 0 or 1. Normalized CV is the normalized cointegration vector of spot and futures prices. Figures in parentheses are p-values. *** indicates statistically significance at 1% level.

Table 2: Estimation results of Markov regime switching model and Markov regime switching model with long run relationship for carbon emission allowances

	MRS		MRS-LR	
$\gamma_{0,1}$	0.0014	(0.012)	-0.1057	(0.018)***
$\gamma_{1,1}$	0.9803	(0.009)***	0.9820	(0.006)***
$\gamma_{2,1}$			-0.2731	(0.037)***
σ_1	0.3080	(0.028)***	0.2986	(0.017)***
$\gamma_{0,2}$	-0.0149	(0.082)	-0.7478	(0.136)***
$\gamma_{1,2}$	0.8680	(0.055)***	0.8646	(0.041)***
$\gamma_{2,2}$			-0.4649	(0.071)***
σ_2	1.4188	(0.167)***	1.2218	(0.100)***
ϕ_1	2.9097	(0.262)***	3.2463	(0.350)***
ϕ_2	-1.8350	(0.329)***	-2.1818	(0.613)***
P_{12}	0.0517		0.0375	
P_{21}	0.1377		0.1014	
Log-L	-877.762		-779.28	
SIC	-905.803		-814.331	
Adj. R^2	0.912		0.936	
S.D.	0.783		0.667	
Skewness	0.007		0.054	
Kurtosis	3.600		3.327	
J-B	16.644***		5.461*	
LB(12)	157.727***		69.779***	
$LB^2(12)$	57.313***		46.836***	

This table provides the estimation results of the Markov regime switching model (MRS) and Markov regime switching model with long-run relationship (MRS-LR) for carbon emission allowances. Figures in parentheses are standard errors. ***, **, * indicate statistical significance at 1%, 5% and 10%, respectively. MRS and MRS-LR models are specified in Equations (11) and (12), respectively. In each state $m = 1, 2$, $\gamma_{0,m}$ are the intercept terms, $\gamma_{1,m}$ represent the slope coefficients for futures returns and $\gamma_{2,m}$ are the slope coefficients associated to lagged basis terms. The logistic function for transition probabilities is specified in Equations (4) and (5). P_{12} gives the probability that state 1 will be followed by state 2 and P_{21} is the probability that state 2 will be followed by state 1. ϕ_1 and ϕ_2 are the unconstrained constant terms in the logistic function, which are estimated along with other unknown parameters using maximum likelihood. Log-L stands for log likelihood. SIC is the Schwartz (1978) Information Criterion. The standard deviation (S.D.), Skewness and Kurtosis are descriptive statistics for the residuals. J-B stands for the Jarque and Bera (1980) test for Normality of residuals. LB(12) and $LB^2(12)$ are Ljung and Box's (1978) Q tests for 12th order autocorrelation in the level and squared residuals, respectively.

Table 3: Estimation results of DCC-GARCH and Markov regime switching DCC model with long run relationship for carbon emission allowances

	DCC-GARCH		MRS-LR-DCC	
Conditional mean equation				
$\mu_{s,1}$	-0.1355	(0.041)***	-0.0935	(0.042)**
$\mu_{f,1}$	-0.0696	(0.034)**	0.0317	(0.035)
$\mu_{s,2}$			-0.2861	(0.113)**
$\mu_{f,2}$			-0.0472	(0.121)
Conditional variance equation				
$\gamma_{s,1}$	1.1234	(0.146)***	0.7054	(0.129)***
$\gamma_{f,1}$	1.1171	(0.137)***	0.7066	(0.129)***
$\alpha_{s,1}$	0.1885	(0.046)***	0.0390	(0.017)**
$\alpha_{f,1}$	0.1828	(0.042)***	0.0379	(0.017)**
$\beta_{s,1}$	0.7911	(0.046)***	0.9412	(0.023)***
$\beta_{f,1}$	0.7967	(0.042)***	0.9426	(0.024)***
$\theta_{1,1}$	0.3304	(0.080)***	0.0000	(0.000)
$\theta_{2,1}$	0.4679	(0.152)***	0.0379	(0.017)**
$\gamma_{s,2}$			1.9076	(0.734)***
$\gamma_{f,2}$			1.8927	(0.633)***
$\alpha_{s,2}$			0.1076	(0.076)
$\alpha_{f,2}$			0.1126	(0.073)
$\beta_{s,2}$			0.9373	(0.036)***
$\beta_{f,2}$			0.9351	(0.036)***
$\theta_{1,2}$			0.0000	(0.000)
$\theta_{2,2}$			0.0379	(0.017)**
Transition parameters				
ϕ_1			-2.4680	(0.277)***
ϕ_2			0.4525	(0.475)
P_{12}			0.0781	
P_{21}			0.3888	
Residual diagnostics				
Log-L	-2431.66		-2255.51	
SIC	-2498.24		-2335.62	
	Spot	Futures	Spot	Futures
S.D.	2.627	2.676	2.634	2.684
Skewness	-0.542	-0.392	-0.317	-0.216
Kurtosis	4.638	4.349	3.074	2.932
J-B	177.493***	112.007***	18.843***	8.850**
LB(12)	9.440	10.041	5.499	4.338
$LB^2(12)$	9.475	5.423	16.663	19.499*

The table provides the maximum likelihood estimates of the DCC-GARCH and MRS-LR-DCC models for carbon emission allowances. Figures in parentheses are standard errors. ***, **, * indicate statistical significance at 1%, 5% and 10%, respectively. The DCC-GARCH (single-regime) and MRS-LR-DCC (two-regime) models are specified in Equations (1)-(9). In each state $m = 1, 2$, $\mu_{i,m}$ are the coefficients for the lagged basis in the conditional mean equations. $\gamma_{i,m}$, $\alpha_{i,m}$, and $\beta_{i,m}$ are the intercept terms, ARCH coefficients, and GARCH coefficients in conditional variances, respectively. $\theta_{i,m}$ are the parameters in the conditional correlation equations. P_{12} gives the probability that state 1 will be followed by state 2 and P_{21} provides the probability that state 2 will be followed by state 1. ϕ_1 and ϕ_2 are the unconstrained constant terms in the logistic function, which are estimated along with other unknown parameters using maximum likelihood. Log-L stands for log likelihood. SIC is the Schwartz (1978) Information Criterion. J-B stands for the Jarque and Bera (1980) test for Normality. LB (12) and LB^2 (12) are Ljung and Box's (1978) Q tests for 12th order autocorrelation in the level and squared residuals, respectively.

Table 4: Effectiveness of Markov regime switching hedge ratios against alternative hedge ratios in carbon emission markets

	Variance	Variance improvement of MRS-LR-DCC	Utility	VaR
Panel A: In-sample hedging effectiveness				
Unhedged	6.9562	92.58%***	-27.825	-43,386.2
Naïve	0.6604	21.85%***	-2.641	-13,367.7
OLS	0.6358	18.83%***	-2.543	-13,117.0
VECM	0.6360	18.86%***	-2.544	-13,119.3
DCC-GARCH	0.6464	20.16%***	-2.585	-13,225.3
MRS	0.6100	15.40%***	-2.440	-12,848.3
MRS-LR	0.6053	14.74%**	-2.421	-12,798.2
MRS-LR-DCC	**0.5161**	**-**	**-2.064**	**-11,817.5**
Panel B: Out-of-sample hedging effectiveness				
Unhedged	9.3685	72.12%***	-37.474	-50,350.1
Naïve	2.9054	10.09%**	-11.621	-28,039.5
OLS	2.8516	8.39%**	-11.407	-27,778.8
VECM	2.8531	8.44%**	-11.412	-27,786.0
DCC-GARCH	3.6636	28.70%**	-14.655	-31,486.3
MRS	2.8135	7.15%**	-11.254	-27,592.4
MRS-LR	2.8019	6.77%**	-11.208	-27,535.5
MRS-LR-DCC	**2.6123**	**-**	**-10.449**	**-26,587.5**

This table provides the hedging effectiveness of Markov regime switching and alternative models in carbon emission markets. The in-sample period is from March 03, 2008 to May 31, 2012 (1109 observations), while the out-of-sample period stems from June 01, 2012 to November 30, 2012 (half a year, 131 observations). Variance denotes the variance of the hedged portfolio. Note that the variance corresponds to logarithmic returns multiplied by 100. Variance improvement of MRS-LR-DCC measures the incremental variance reduction of the MRS-LR-DCC model over the other models. Asterisks ***, ** ,* indicate statistical significance in the variance improvement of the MRS-LR-DCC model at 1%, 5% and 10% levels, respectively, with p-values provided from White's (2000) Reality Check using the stationary bootstrap of Politis and Romano (1994). Utility is the average daily utility for an investor with a mean-variance utility function and a coefficient of risk aversion of 4, using different hedging strategies. VaR is the value-at-risk figure (in Euros) estimated with z_a equal to the normal distribution 5% quantile value.

Table 5: Effectiveness long/short hedging positions of Markov regime switching hedge ratios against alternative hedge ratios in carbon emission markets

	In-sample hedging effectiveness				Out-of-sample hedging effectiveness			
	Semi-variance	Semi-variance improvement of MRS-LR-DCC	Semi-utility	VaR	Semi-variance	Semi-variance improvement of MRS-LR-DCC	Semi-utility	VaR
Panel A: Short hedgers positions								
Unhedged	3.7935	94.00%***	-15.174	-32039.5	4.1018	96.09%***	-16.407	-33,913.1
Naïve	0.3229	29.50%***	-1.292	-9,347.6	0.5734	72.02%***	-2.293	-12,455.9
OLS	0.3103	26.63%***	-1.241	-9,163.1	0.5202	69.17%***	-2.081	-11,864.6
VECM	0.3104	26.66%***	-1.242	-9,164.9	0.5223	69.29%***	-2.089	-11,889.0
DCC-GARCH	0.3059	25.58%***	-1.224	-9,098.1	0.5353	70.03%***	-2.141	-12,035.2
MRS	0.2975	23.48%***	-1.190	-8,972.4	0.4660	65.58%***	-1.864	-11,229.3
MRS-LR	0.2984	23.71%***	-1.194	-8,985.8	0.4468	64.10%***	-1.787	-10,995.5
MRS-LR-DCC	**0.2276**	**-**	**-0.911**	**-7,848.5**	**0.1604**	**-**	**-0.642**	**-6,588.1**
Panel B: Long hedgers positions								
Unhedged	3.1680	90.90%***	-12.672	-29,279.2	5.1951	52.83%***	-20.781	-37,494.2
Naïve	0.3239	14.47%**	-1.347	-9,547.6	2.3099	-6.10%	-9.240	-25,001.5
OLS	0.3250	11.34%**	-1.300	-9,331.9	2.3097	-6.11%	-9.239	-25,000.3
VECM	0.3251	11.37%**	-1.300	-9,379.3	**2.3090**	**-6.14%**	**-9.236**	**-24,996.6**
DCC-GARCH	0.3399	15.23%***	-1.360	-9,590.5	3.1120	21.25%**	-12.448	-29,079.4
MRS	0.3120	7.65%**	-1.248	-9,188.4	2.3266	-5.33%	-9.307	-25,091.7
MRS-LR	0.3064	5.96%**	-1.226	-9,105.3	2.3347	-4.97%	-9.339	-25,135.2
MRS-LR-DCC	**0.2881**	**-**	**-1.153**	**-8,830.0**	2.4508	-	-9.803	-25,752.3

This table provides the hedging effectiveness of long/short hedging positions of the Markov regime switching and alternative models in carbon emission markets. The in-sample period is from March 03, 2008 to May 31, 2012 (1109 observations), while the out-of-sample period stems from June 01, 2012 to November 30, 2012 (half a year, 131 observations). Semi-variance denotes the semi-variance of the hedged portfolio. Note that the semi-variance corresponds to logarithmic returns multiplied by 100. Semi-variance improvement of MRS-LR-DCC measures the incremental semi-variance reduction of the MRS-LR-DCC model over the other models considered. Asterisks ***, ** ,* indicate statistical significance in the variance improvement of the MRS-LR-DCC model at 1%, 5% and 10% levels, respectively, with p-values provided from White's (2000) Reality Check using the stationary bootstrap of Politis and Romano (1994). Semi-utility is the average daily semi-utility for an investor with a mean-semi-variance utility function and a coefficient of risk aversion of 4, using different hedging strategies. VaR is the value-at-risk figure (in Euros) estimated with z_a equal to the normal distribution 5% quantile value and σ equal to the semi-variance of the hedged portfolio.

Appendix A: Estimation procedure for the MRS-LR-DCC model

We follow Lee and Yoder's (2007a) recombination procedures for estimating the MRS-LR-DCC model. For example, the conditional variance and conditional residuals of the spot returns are recombined as

$$h_{s,t}^2 = \pi_{1,t}(r_{s,1,t}^2 + h_{s,1,t}^2) + (1-\pi_{1,t})(r_{s,2,t}^2 + h_{s,2,t}^2) - [\pi_{1,t} r_{s,1,t} + (1-\pi_{1,t}) r_{s,2,t}]^2 \tag{A.1}$$

$$e_{s,t} = \Delta S_t - [\pi_{1,t} r_{s,1,t} + (1-\pi_{1,t}) r_{s,2,t}] \tag{A.2}$$

where $\pi_{1,t}$ is the probability of being in state 1 at time t and $1-\pi_{1,t}$ the probability of being in state 2 at time t; $r_{s,m,t}$ is the state-dependent conditional mean equation of the spot returns. Lee and Yoder (2007b) further recombine the conditional correlation as[12]

$$\begin{aligned}\rho_t = \frac{1}{h_{s,t} h_{f,t}} \{ & [\pi_{1,t}(r_{s,1,t} r_{f,1,t} + \rho_{1,t} h_{s,1,t} h_{f,1,t}) + (1-\pi_{1,t})(r_{s,2,t} r_{f,2,t} + \rho_{2,t} h_{s,2,t} h_{f,2,t})] \\ & -[\pi_{1,t} r_{s,1,t} + (1-\pi_{1,t}) r_{s,2,t}][\pi_{1,t} r_{f,1,t} + (1-\pi_{1,t}) r_{f,2,t}]\}\end{aligned} \tag{A.3}$$

After the recombination procedures shown in Equations (A.1)-(A.3), the MRS-LR-DCC model is path-independent, as the variance-covariance matrix is not dependent on all the past information but on current regime. The model is then estimated through maximum likelihood. The density function mixed with the probability distribution of the state variable is shown as

$$f(\mathbf{X}_t;\boldsymbol{\theta}) = \frac{\pi_{1,t}}{2\pi} |\mathbf{H}_{1,t}|^{-1/2} \exp(-\frac{1}{2}\mathbf{e}_{1,t}^{'}\mathbf{H}_{1,t}^{-1}\mathbf{e}_{1,t}) + \frac{(1-\pi_{1,t})}{2\pi} |\mathbf{H}_{2,t}|^{-1/2} \exp(-\frac{1}{2}\mathbf{e}_{2,t}^{'}\mathbf{H}_{2,t}^{-1}\mathbf{e}_{2,t}) \tag{A.4}$$

where $\boldsymbol{\theta}$ is the vector of unknown parameters and $\pi_{1,t}$, $\mathbf{H}_{m,t}$ and $\mathbf{e}_{m,t}$ are defined as before. The unknown parameter vector $\boldsymbol{\theta}$ can be estimated by maximizing the following log-likelihood function

$$L(\boldsymbol{\theta}) = \sum_{t=1}^{T} \log f(\mathbf{X}_t;\boldsymbol{\theta}) \tag{A.5}$$

L($\boldsymbol{\theta}$) subjects to the constraint that $0 \le \pi_{1,t} \le 1$ and is maximized using the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm. When $\pi_{1,t} = 1$, the MRS-LR-DCC model collapses to the DCC-GARCH model of Engle (2002). When all the conditional variance parameters are set to zero, the MRS-LR-DCC model collapses to the standard Markov regime switching model (MRS) in the mean equation.

[12] For additional details of the collapsing methods for conditional residuals, conditional variances, conditional covariance and conditional correlations, see Gray (1996) and Lee and Yoder (2007a, 2007b).