Risk Spillovers across the Energy and Carbon Markets and Hedging Strategies for Carbon Risk

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Abstract

This study examines the risk spillovers between energy futures prices and Europe-based carbon futures contracts. We use a Markov regime-switching dynamic correlation, generalized autoregressive conditional heteroscedasticity (MS-DCC-GARCH) model in order to capture the time variations and structural breaks in the spillovers. We further evaluate the optimal weights, hedging effectiveness, and dynamic hedging strategies for the MS-DCC-GARCH model based on both the regime dependent and regime independent optimal hedge ratios. We finally complement our analysis by examining the in- and out-of sample hedging performances for alternative strategies. Our results mainly show significant volatility and time-varying risk transmission from energy markets to carbon market. We also find that spot and futures segments of the emission markets exhibit time-varying correlations and volatile hedging effectiveness. The subsample estimates show significant changes in the hedge effectiveness over the different phases of the European carbon market. These results have important investment and policy implications.

JEL Classification: C32, G11, G19, Q47, Q54.
Keywords: Multivariate regime-switching; time-varying correlations; hedging; CO_2 allowance prices

Highlights

- Risk spillovers between energy and carbon futures prices are studied.
- We make use of a Markov regime-switching DCC-GARCH.
- Optimal weights, hedging effectiveness, and dynamic hedging strategies are evaluated.
- There exists significant time-varying risk transmission from energy to carbon markets.
- Carbon spot and futures segments exhibit volatile hedging effectiveness.

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1. Introduction

The links between energy consumption and greenhouse gas emissions have important implications for economic growth, the environment and the quality of human life. Fast economic growth may produce emissions that can lead to the degradation of the environment, which in turn affects human health and reduces the quality of life. About 77% of all greenhouse gases at the global level are currently accounted for by carbon dioxide (CO_2) emissions and 75% of these CO_2 emissions come from the use of fossil fuels (coal, natural gas and oil) in energy production, transportation, industrial processes and land-use changes.

These challenging global environmental issues have led many developed and developing countries to accept legally binding limitations, reductions and obligations in their greenhouse gas emissions as set by the Kyoto Protocol, which was ratified in 1997 by the parties to the United Nations Framework Convention on Climate Change (UNFCCC).[1] The Kyoto Protocol has motivated the creation of emissions trading schemes and new carbon markets. The "carbon markets" were established to help accommodate compliance with the set targets by allowing the participants to buy/sell allowances.[2] The EU Emission Trading Scheme (EU ETS) is the largest carbon trading market in the world that has been created to comply with the Kyoto Protocol.[3] To reduce the costs of compliance with this protocol, the European Commission linked in 2003 the Kyoto mechanisms and the EU ETS which led to an amendment to the ETS-Directive (EU, 2004). According to the 'Linking Directive', the EU member countries are allowed to use some credits generated by the Clean Development Mechanism (CDM), called Certified Emission Reduction

[1] The Protocol has two commitment periods which apply to carbon emissions during the periods 2008-2012 and 2013-2020, respectively. However, the Protocol's amendment for the second commitment period has not entered into legal force.

[2] Currently, there exist several regional markets with spot and futures contract trading on CO_2 allowances. These include BlueNext (France, closed on December 5, 2013), the Nordpool (runs the leading power market in Europe which is now owned by NASDAQ), the Chicago Climate Exchange (CCX, recently acquired by Intercontinental Exchange, ICE), the Netherlands-based European Climate Exchange, listed in the London Stock Exchange), and the European Energy Exchange (EEX, based in Leipzig, Germany).

[3] The EU-ETS is a cap-and–trade system for greenhouse gas emission (GHG) allowances. It has three distinct trading periods: Phase I (2005 to 2007), Phase II (2008 to 2012 corresponding to the Kyoto Protocol commitment period), and Phase III (2012 to 2020).

(CER), and the Joint Implementation (JI), called Emission Reduction Units (ERU), up to a certain amount to meet their obligations (Nazifi, 2013). Linking the EU ETS to the CDM indicates the recognition of CERs as equivalent to European Union Allowances (EUAs), making the CERs fully fungible for compliance within the EU ETS.

Due to the emergency of regulations of carbon emissions not only in the US and the EU but also in other parts of the world (e.g., Australia, New Zealand and Asia), carbon risk will become increasingly important for an increasing number of companies. Utilities are the most affected sector given their highest emission intensity, emitting for example 40% of carbon pollution in the EU. The utilities are not subject to direct international competition and do not receive the same political support as the other energy-intensive sectors, making carbon risk management a higher priority for a number of big companies in this sector. It is thus clear that achieving emission targets for 2020 and 2050 in an effective manner requires not only a continuation of the trading schemes, but also an adaptation of large number firms to the regulatory environment and development of risk management strategies for carbon risk.

While it will ease the adjustment of the firms to emission caps, help the continuation of efficient CO_2 reduction path, and protect the interest of corporate stakeholders, managing carbon risk is however a challenging task. Indeed, successful risk management requires dynamic portfolio management practices since the environment surrounding carbon trading is subject to significant uncertainty owing to regulatory changes, climate change, and interaction with prices of energy sources such as crude oil, natural gas, coal, and electricity. These uncertainties and changes also induce significant nonlinear dynamics into carbon prices such as time-variation and regime-dependence.

Our study addresses the issue of carbon risk hedging by considering the volatility interactions not only between the carbon spot and futures of the EUA and CER markets, but also between these carbon markets and primary energy markets. It also derives dynamic hedging strategies for carbon risk based on suitable models. To do so, we adopt a Markov regime-switching GARCH model with dynamic conditional correlations (MS-DCC-GARCH). This model allows one to capture both the time-variation in conditional volatility of the markets under consideration according to different regimes and their dynamic links (correlations), which are driven by regulatory changes and demand/supply shocks. Our MS-DCC-GARCH-based results for the in-sample and out-of-sample hedging effectiveness of the carbon futures contracts as well as the risk spillovers between the energy and carbon prices provide useful guidance for the implementation of effective carbon risk management and policy regulations.

The remainder of the study is organized as follows. Section 2 presents a brief review of the literature on carbon markets, with a focus on risk management and the methodology. Section 3 describes the data used and reports the empirical findings. Section 4 discusses the results. Finally, Section 5 concludes the paper and provides policy implications.

2. Methodology

2.1. Literature review

The literature on carbon markets has grown rapidly in recent years. To date, a number of studies have examined the economic and energy price drivers of carbon allowances prices (e.g., Mansanet-Bataller et al., 2007; Alberola et al., 2008; Keppler and Mansanet-Bataller, 2010; Kim and Koo, 2010; Bredin and Muckley, 2011; Creti et al., 2012; Aatola et al., 2013; Lutz al., 2013; Sousa and Aguiar-Conraria, 2014). This strand of research generally shows that carbon prices are significantly affected by economic aggregate variables (e.g., industrial production), weather conditions (e.g., temperature index), and prices of primary energy commodities such as coal, crude oil, electricity, and natural gas. For example, Keppler and Mansanet-Bataller (2010) find evidence suggesting that electricity prices Granger-cause the CO_2 prices. Bredin and Muckley (2011) use cointegration techniques to investigate the equilibrium relationship between carbon futures prices and fundamentals such as energy spreads for electricity production, the Euro Stoxx 50, the Eurostat index of industrial production, the oil price and a temperature index. These authors find evidence of a new pricing regime emerging in Phase 2 of the EU ETS and a maturing carbon market driven by the fundamentals. In a related study, Creti et al. (2012) investigate the determinants of carbon prices during the two phases of EU ETS. The authors show that although the oil and equity prices are significant determinants of carbon prices in both phases, the switching price between natural gas and coal is only important in the second phase.

In addition to the above studies that focus on the drivers of carbon allowances prices, the existing literature also examines two other major issues: *i*) the stochastic properties, market efficiency, price discovery, and spot-futures price relationship in the carbon spot and futures markets (e.g., Daskalakis and Markellos, 2008; Seifert et al., 2008; Milunovich and Joyeux, 2010; Arouri et al., 2012); and *ii)* the volatility transmission between carbon spot and futures markets as well as the links between energy prices and and carbon prices (e.g., Rittler, 2012; Aatola et al., 2013; Lutz al., 2013).

The issue of carbon risk management is much less explored in terms of both scope and methodology. For instance, Pinho and Madaleno (2010) estimate the optimal hedge ratios for the European Climate Exchange from the multivariate GARCH and OLS models and the naïve strategy. Their results indicate that dynamic hedging provides superior gains (in reducing the portfolio variance), compared to those obtained from static hedging, when adjustment costs are not taken into consideration. Those authors also find that utility gains increase with investor's increased preference over risk. More recently, Fan et al. (2014) estimate the hedge ratios and examine the hedging effectiveness in the EU-ETS carbon market. They compare the estimated hedge ratios for the CO_2 markets with those derived for other markets, and find that despite the uniqueness of the carbon market the results are consistent with those found in other markets.

Overall, the scarcity of studies on estimation of hedge ratios for carbon assets and novelty of the carbon market provide a compelling motivation for us to examine optimal hedge ratios and hedging strategies for carbon risk.

2.2. The models

The dynamic conditional correlation (DCC) model proposed in this study is constructed along the lines of Billio and Caporin (2005), Lee (2010) and Chang et al. (2011) which examine oil and financial markets. Let $R_t = [R_{c,t}, R_{f,t}, R_{e,t}, R_{n,t}, R_{l,t}]'$ be the (5×1) vector of returns where $R_{c,t}$ ($R_{f,t}$) is the CO_2 emission spot (futures) return, and $R_{e,t}$, $R_{n,t}$, and $R_{l,t}$ are the returns on the nearby electricity, natural gas and coal futures contracts, respectively. The GARCH specification for the volatility spillover model follows Ling and McAleer (2003) and is specified as

$$\begin{aligned} R_t &= \Phi_0 + \sum_{i=1}^{p} \Phi_i R_{t-i} + \varepsilon_t \\ \varepsilon_t &= D_t z_t \end{aligned} \qquad \mathbf{(1)}$$

where $D_t = \mathrm{diag}(h_{c,t}^{1/2}, h_{f,t}^{1/2}, h_{e,t}^{1/2}, h_{n,t}^{1/2}, h_{l,t}^{1/2})$ is the vector of the conditional volatility terms. The conditional mean of the return vector R_t is specified as a vector autoregressive process of order p with (5×5) parameter matrices Φ_i, $i = 1,2,...,p$. The unexplained component ε_t follows a GARCH specification described as $\varepsilon_t \mid \psi_{t-1} \sim ID(0, P_t)$ where P_t is the time-varying variance-covariance matrix. Denoting the conditional variance matrix as $H_t = [h_{c,t}, h_{f,t}, h_{e,t}, h_{n,t}, h_{l,t}]'$, we impose the following specification which allows for volatility spillover in the model

$$H_t = c + A\varepsilon_{t-1}^{(2)} + BH_{t-1} \qquad \mathbf{(2)}$$

where c is a (5×1) vector of constants, A and B are (5×5) matrices for the ARCH and GARCH effects and $\varepsilon_t^{(2)} = [\varepsilon_{c,t}^2, \varepsilon_{f,t}^2, \varepsilon_{e,t}^2, \varepsilon_{n,t}^2, \varepsilon_{l,t}^2]'$. Note that the non-diagonal forms of the matrices A and B allow volatility spillovers across the series. Following Engle (2002), we allow conditional correlations to vary over time by specifying the variance-covariance matrix $P_t = D_t \Gamma_t D_t$ with Γ_t specified as the conditional correlation matrix.

In our model, however, the conditional correlation matrix is regime-switching as governed by a discrete Markov process and is defined as $\Gamma_t = \mathrm{diag}\{Q_t\}^{-1/2} Q_t \mathrm{diag}\{Q_t\}^{-1/2}$. In order to incorporate regime shifts into the DCC model specified in Equations (1) and (2), we follow Billio and Caporin (2005) and introduce a Markov regime-switching dynamic correlation model by specifying Q_t as

$$Q_t = [1-\alpha(s_t)-\beta(s_t)]\bar{Q} + \alpha(s_t)\varepsilon_{t-1}^{(2)} + \beta(s_t)Q_{t-1} \qquad \textbf{(3)}$$

where $\bar{Q}$ is the unconditional covariance matrix of the standardized residuals, $\alpha(s_t)$ and $\beta(s_t)$ are the regime-dependent parameters that control the regime-switching system dynamics, $s_t \in \{1, 2\}$ is the state or regime variable following a first-order, two-state discrete Markov process. Note that the variances in this specification are regime-independent, whereas the covariances (or correlations) are both time-varying and regime-switching.[4] As Billio and Caporin (2005) note, the specification in which all parameters are regime dependent is highly unstable due to the large number of switching parameters. Therefore, we restrict the regime dependent structure to the time-varying correlations only. Thus, the model allows both volatility spillover and regime-switching dynamic correlations. The specification is then completed by defining the transition probabilities of the Markov process as $p_{ij} = P(s_{t+1} = i \mid s_t = j)$. Thus, p_{ij} is the probability of being in regime *i* at time *t*+1 given that the market was in regime *j* at time *t*, where the regimes *i* and *j* take values in {1, 2}. Finally, the transition probabilities satisfy $\sum_{i=1}^{2} p_{ij} = 1$.

[4] We estimate the MS-DCC-GARCH model using the two step approach of Engle and Sheppard (2001) and Engle (2002). In the second step, we use the modified Hamilton filter proposed by Caporin and Billio (2005) to solve the path-dependence problem (Cai, 1994; Hamilton and Susmel, 1994; Gray, 1996) and estimate the regime-switching conditional covariances.

We employ two hedging strategies for the combined spot and futures portfolio based on the results of the MS-DCC-GARCH model. These are the minimum-variance hedge ratio and the optimal weights (Kroner and Ng, 1998; Hammoudeh et al. 2010).

3. Empirical Findings

3.1. Data

We use daily data for European Union Allowances (EUA) and Certified Emission Reduction (CER) spot and futures prices, obtained from the Thomson Reuters Datastream database. The CER market data covers the period from December 1, 2009 to May 12, 2014 with 1,390 observations.[5] Since Phase I is the test period, the data period for the EUA market starts with Phase II (the commitment phase) of the European Union ETS (EU Emission Trading System) and covers the period from April 15, 2008 to May 12, 2014 with 1,585 observations. Futures data series are constructed using the December contract prices for the EUA and CER contracts.

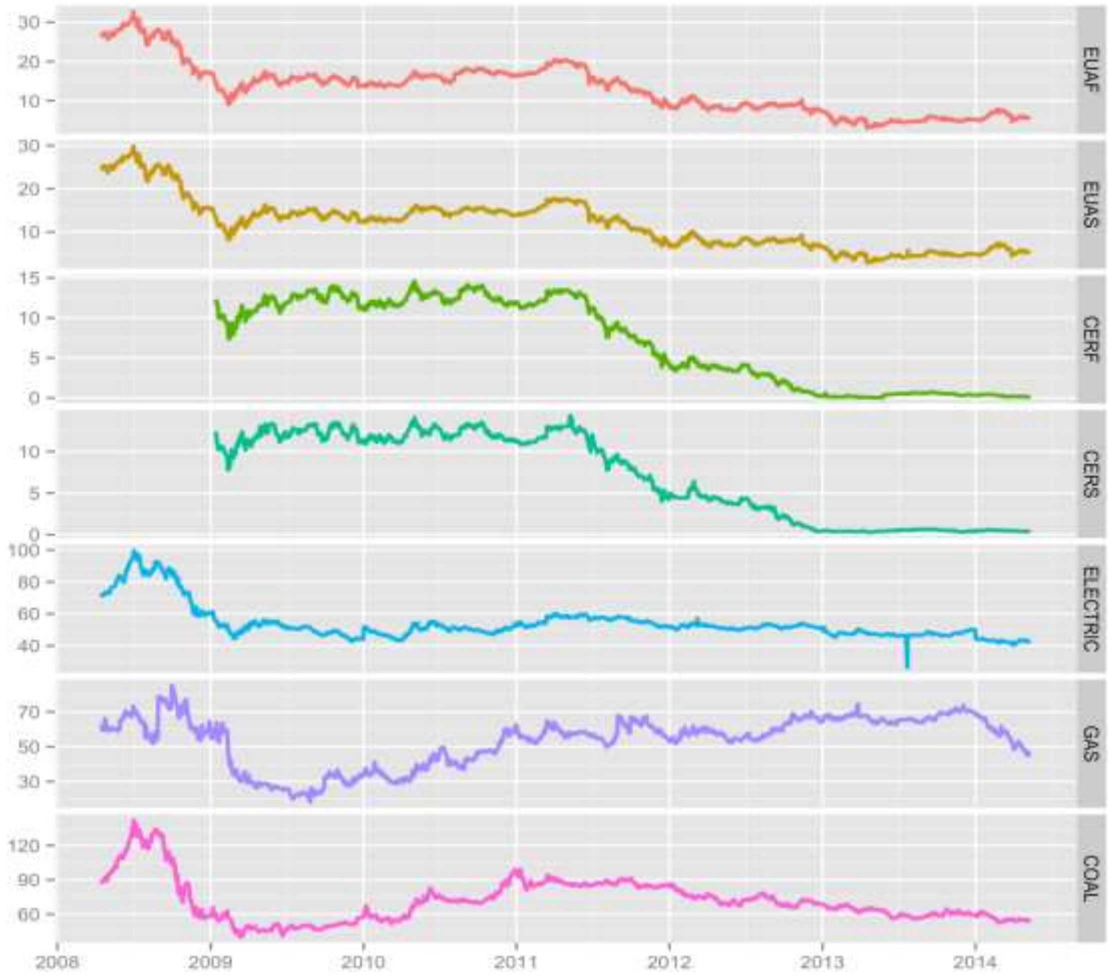
In addition to the EUA market futures and spot prices (*EUAF* and *EUAS*) and the CER market futures and spot price (*CERF* and *CERS*) data, we utilize in the volatility spillover model several energy futures market-related variables to examine the source of the carbon emissions. The energy futures prices include: (i) the EEX (European Energy Exchange) electricity futures prices (*ELECTRIC*); (ii) the ARA (Argus/McCloskey) coal futures prices (*COAL*); and (iii) the ICE (international Commodities Exchange) UK natural gas futures prices (*GAS*). The inclusion of these variables allows us to examine possible risk spillovers from energy markets at large to the carbon emission market. The risk spillovers across the energy markets expectedly arise from common risk factors driving the price dynamics in these markets such as economic growth trends, regulatory changes, technology shifts, and fuel substitution. In short, our volatility spillover model includes

[5] The shorter sample period for the CER market is due to data availability as trading on this market started only in 2008.

the carbon spot and futures prices as well as the futures settlement prices for electricity, coal, and natural gas.

Figure 1 provides the time series plots for the daily futures and spot energy and carbon prices. Not surprisingly, we observe a general negative effect of the 2007-2008 global financial crisis on the energy market, most likely due to the severe economic downturn that prevailed during that period. A similar downward trend is also observed since the mid-2011 in both the EUA and CER carbon emission markets, which seems to coincide with the prolonged crisis in the euro-zone that has led to a widespread economic slowdown, thereby driving energy demand down.

Figure 1. Time-variations of carbon spot and futures prices (EUAS, EUAF, CERS, and CERF), electricity price (ELECTRIC), natural gas price (GAS), and coal price (COAL)



Note: *EUAF* (*CERF*) and *EUAS* (*CERS*) refer to the EUA (CER) market futures and spot prices, respectively.

Table 1 provides the descriptive statistics for the log-returns.[6] We see that the CER carbon market experiences the greatest volatility in price changes relative to the EUA and energy prices. Nazifi (2013) notes a lack of competitive conditions in these markets, access constraints on the use and the availability of CERs, regulatory changes regarding both EUAs and CERs, and uncertainty surrounding CERs. It is also interesting to note that China is the biggest supply country in primary CER market. All return series have kurtosis values higher than the normal distribution, implying the presence of extreme movements in either direction.

Table 1. Descriptive statistics for returns (%)

	EUAF	EUAS	CERF	CERS	ELECTRIC	GAS	COAL
Mean	-0.10%	-0.10%	-0.33%	-0.25%	-0.03%	-0.10%	-0.10%
S.D.	3.27%	3.53%	9.47%	4.12%	2.34%	3.27%	3.53%
Min	-41.71%	-43.00%	-99.16%	-29.55%	-56.00%	-41.71%	-43.00%
Max	21.85%	28.70%	225.13%	30.11%	56.00%	21.85%	28.70%
Skewness	-1.15%	-0.93%	9.17%	-0.55%	0.13%	-1.15%	-0.93%
Kurtosis	20.37%	21.96%	255.21%	11.59%	410.89%	20.37%	21.96%
JB	27807.20***	32155.40***	3800083.06***	7866.60***	11171448.59***	74261.85***	2380.39***
$Q(1)$	3.71*	0.02	18.32***	0.01	201.34***	1.12	24.29***
$Q(5)$	55.78***	40.10***	24.24***	4.00	202.36***	22.46***	28.42***
ARCH(1)	18.25***	50.60***	2.03	39.74***	391.09***	0.12	44.59***
ARCH(5)	49.29***	61.31***	2.02	78.74***	645.37***	5.91	214.86***
n	1585	1585	1390	1390	1585	1585	1585

Note: This table gives the descriptive statistics for logarithmic returns. *EUAF* (*CERF*) and *EUAS* (*CERS*) refer to the EUA (CER) market futures and spot prices, respectively. In addition to the mean, the standard deviation (S.D.), minimum (min), maximum (max), skewness, and kurtosis statistics, the table reports the Jarque-Bera normality test (JB), the Ljung-Box first [$Q(1)$] and the fourth [$Q(5)$ autocorrelation tests, and the first [ARCH(1)] and the fourth [ARCH(5)] order Lagrange multiplier (LM) tests for the autoregressive conditional heteroscedasticity (ARCH). The asterisks ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

3.2. Empirical results

3.2.1. Model identification tests

As stated in Section 2, we estimate the regime-specific and time-varying correlations in the MS-DCC-GARCH model specified in Equations (1)-(2) by adopting the two-step approach proposed by Engle (2002) and Engle and Sheppard (2001). Then, in order to compare the findings

[6] Descriptive statistics for the variables in the levels can be made available upon request.

from the MS-DCC-GARCH model with the static alternative, we also estimate a constant parameter DCC-GARCH model as the benchmark.[7]

The MS-DCC-GARCH model needs a prior specification of the number of regimes and, given that the number of regimes is known, the likelihood is evaluated using the filtering procedure of Hamilton (1990), with the modification suggested by Caporin and Billio (2005), followed by the smoothing algorithm of Kim (1994). Once the model's parameters and transition probabilities (p_{ij}) are obtained, the conditional moments of the MS-DCC-GARCH model in Equation (3) as well as the optimal hedge ratio and the optimal portfolio weights are computed by using the predictive probabilities $p_{i,t} = P(s_t = i \mid \psi_{t-1})$ i=1,2, that are obtained from the transition probabilities $p_{ij} = P(s_{t+1} = i \mid s_t = j)$, i,j =1,2, and the filtered probabilities $p_{i,t-1} = P(s_{t-1} = i \mid \psi_{t-1}]$, i=1,2, of the modified Hamilton filter.[8] Note that we select the number of regimes in both models by using the likelihood ratio (LR) tests with the upper bound for the p-values obtained according to Davies (1987), and supplement the latter with Akaike (AIC), Bayesian (BIC), and Hannan-Quinn (HQ) information criteria.

We specify the order of the vector autoregressive component in Equation (1) based on the AIC. The results select p=5 for the EUA market model and p=3 for the CER market model. As to the GARCH orders, we first estimate a univariate autoregressive GARCH (AR-GARCH) model for each series and perform several diagnostic tests for possible misspecification. Table 2 presents diagnostic test results. The AR order p is identified as 3 for CERF and CERS series and 5 for the other series. The Lagrange multiplier (LM) ARCH(1) test results show that GARCH(1,1) specification is sufficient to capture the conditional variance in all series except for EUA spot returns. However, when a multivariate model is estimated as specified in Equations (1)-(2), the

[7] The two-step estimation procedure of Engle (2002) and Engle and Sheppard (2001) is also adopted for the DCC-GARCH model. Non-diagonal matrices A and B allow for volatility spillovers across the series.

[8] Given the transition probability matrix P and the vector of filtered probabilities p_{t-1}, the vector of predictive probabilities is obtained as $p_t = P \cdot p_{t-1}$.

diagnostics indicate no remaining ARCH(1) in the residual for this series as well.[9] The results of the Ljung-Box Q(p) tests indicate no autocorrelation at order p=10 and p=20. The return series are not normally distributed as indicated by the Jarque-Bera (JB) normality tests. Based on the evidence in Table 2, we specify the GARCH component of the model in Equations (1)-(2) as GARCH(1,1).

Table 2. Univariate AR(p)-GARCH(1,1) fit diagnostics

	ARCH-LM(1)	JB	Q(10)	Q(20)
EUAF	0.0636	937***	9.3072	17.7365
	(0.8009)	(0.0000)	(0.4094)	(0.5401)
EUAS	7.2466***	2717***	11.1058	17.7378
	(0.0072)	(0.0000)	(0.2685)	(0.5400)
CERF	0.0014	16041953***	2.6003	11.0213
	(0.9699)	(0.0000)	(0.9781)	(0.9231)
CERS	1.0289	8068***	6.7980	16.0379
	(0.3106)	(0.0000)	(0.6581)	(0.6547)
ELECTRIC	0.2295	17725620***	9.9844	13.9466
	(0.6319)	(0.0000)	(0.3517)	(0.7868)
GAS	0.0544	5375***	9.03887	14.3744
	(0.8156)	(0.0000)	(0.4337)	(0.7614)
COAL	0.1874	376***	5.2031	12.1432
	(0.6651)	(0.0000)	(0.8162)	(0.8794)

Note: The table reports diagnostic tests for univariate autoregressive GARCH model fits. An AR(p)-GARCH(1,1) model is fitted to each series. The AR order p is 3 for CERF and CERS series and 5 for the others. Table reports the Jarque-Bera normality test (JB), the Ljung-Box first [Q(10)] and the fourth [Q(20) autocorrelation tests, and the first [ARCH(1)] order Lagrange multiplier (LM) tests for the autoregressive conditional heteroscedasticity (ARCH). The p-values of the tests are given in parentheses. The asterisks ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

After specifying the VAR and GARCH orders in Equations (1)-(2), we next estimate a non-regime-switching DCC-GARCH model and the MS-DCC-GARCH alternative with 2 regimes in order test the presence of nonlinearity or regime-switching. The LR nonlinearity tests for the EUA and CER market models are reported in Tables 3 and 4, respectively. They strongly reject the non-switching DCC-GARCH model in favor of the MS-DCC-GARCH model with 2 regimes for both

[9] The value of the LM ARCH(1) test for the residual of the EUAS return series in Equations (1)-(2) is 0.8602 with a p-value of 0.3537.

Table 3. Estimates of the MS-DCC-GARCH model for the EUA market

Variance parameters	*Equations*				
	EUAF	EUAS	ELECTRIC	GAS	COAL
c_i	0.9523*** (0.2690)	0.9371*** (0.1073)	2.1690*** (0.1774)	0.2189*** (0.0181)	0.0015 (0.0139)
a_{i1}	0.1314*** (0.0251)	0.1155*** (0.0244)	-0.0858 (0.0552)	0.1216*** (0.0104)	0.0306*** (0.0095)
a_{i2}	0.0933*** (0.0233)	0.1119*** (0.0141)	0.0545 (0.0518)	-0.1109*** (0.0104)	-0.0191* (0.0102)
a_{i3}	0.1794*** (0.0424)	0.1864*** (0.0348)	0.1193*** (0.0191)	-0.0330*** (0.0082)	-0.0175*** (0.0027)
a_{i4}	-0.0526 (0.0339)	-0.0783** (0.0377)	0.0305*** (0.0112)	0.0802*** (0.0208)	0.0027 (0.0051)
a_{i5}	0.0551 (0.0357)	0.0409 (0.0292)	0.0698*** (0.0180)	-0.1237*** (0.0284)	0.0655*** (0.0089)
b_{i1}	0.4123*** (0.0490)	0.2329*** (0.0130)	-0.5378*** (0.0344)	-1.3416*** (0.2181)	-0.5101*** (0.1545)
b_{i2}	0.2924*** (0.0224)	0.4634*** (0.0415)	-0.4418*** (0.0404)	1.3801*** (0.2433)	0.5038*** (0.1397)
b_{i3}	-0.67* (0.3808)	-0.2226** (0.1044)	0.6519*** (0.0466)	0.7989*** (0.0520)	0.1335*** (0.0112)
b_{i4}	1.2343*** (0.3702)	1.1447*** (0.3141)	-1.8942*** (0.2346)	0.8825*** (0.0071)	0.0010 (0.0276)
b_{i5}	-1.3037*** (0.2937)	-1.1701*** (0.2049)	1.2981*** (0.2998)	0.1385*** (0.0024)	0.8938*** (0.0127)
DCC parameters					
$\alpha(s_t=1)$	0.0272*** (0.0055)		*Regime properties*		
$\beta(s_t=1)$	0.7546*** (0.0662)		Observations	Prob.	Duration
$\alpha(s_t=2)$	0.1622*** (0.0060)	Regime 1	1392.50	0.880	12.770
$\beta(s_t=2)$	0.4284*** (0.0732)	Regime 2	191.50	0.120	1.750
	MS DCC GARCH	DCC GARCH			
log L	-13592.843	-17204.974		*Transition probabilities*	
AIC	17.216	21.749		Regime 1	Regime 2
HQ	17.269	21.774	Regime 1	0.922	0.572
BIC	17.358	21.817	Regime 2	0.078	0.428
LR linearity test		7224.2622*** (0.0000) [0.0000]			

Note: This table reports the estimates of the MS-DCC-GARCH model given in Equations (1)-(3). The GARCH part of the model is specified as a GARCH(1,1). The MS-DCC-GARCH model is estimated using the maximum likelihood (ML) method. The likelihood ratio (LR) linearity test is reported with *p*-value in parentheses. The *p*-value of the Davies (1987) test is also given in the square brackets. Standard errors of the estimates are given in parentheses. HQ stands for the Hannan-Quinn information criterion, BIC for the Bayesian information criterion, and log L for the log likelihood. ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Estimates of the MS-DCC-GARCH model for the CER market

Variance parameters	*Equations*				
	CERF	CERS	ELECTRIC	GAS	COAL
c_i	62.8379*** (8.9844)	1.6318*** (0.1164)	3.4944*** (0.1364)	0.0049 (0.0960)	0.1497** (0.0751)
a_{i1}	0.3443*** (0.0148)	0.0069 (0.0079)	0.0010 (0.0070)	-0.0053*** (0.0015)	0.0014 (0.0052)
a_{i2}	0.0597 (0.1403)	0.3178** (0.1436)	0.0276*** (0.0025)	0.0246 (0.0198)	0.0134 (0.0417)
a_{i3}	-0.1464 (0.0993)	-0.2377** (0.1112)	0.0474*** (0.0099)	-0.0326 (0.0260)	-0.0107 (0.0161)
a_{i4}	0.6030 (0.7086)	0.0825 (0.0782)	-0.0119 (0.0455)	0.3195*** (0.1040)	0.0104 (0.0110)
a_{i5}	-0.9288 (0.6989)	0.0020 (0.1840)	-0.0828 (0.0606)	0.1437 (0.1235)	0.0433 (0.0439)
b_{i1}	0.0622* (0.0366)	0.0194 (0.0618)	-0.6890*** (0.1557)	0.0726** (0.0333)	-0.3954 (0.2773)
b_{i2}	1.8040 (1.1559)	0.7580*** (0.0054)	-0.9058 (0.9344)	-0.2088*** (0.0102)	-0.0679 (0.0657)
b_{i3}	-13.6993** (6.4001)	-0.4510*** (0.1733)	0.3145*** (0.0046)	0.4985 (0.3425)	-0.1210*** (0.0064)
b_{i4}	-6.7378 (5.6436)	-1.6606*** (0.4363)	-0.9223** (0.4446)	0.6625*** (0.0500)	-0.0949* (0.0575)
b_{i5}	-15.6505 (10.5654)	-0.4867 (0.5343)	-0.1287 (0.1469)	0.7210* (0.3852)	1.0184*** (0.1378)

DCC parameters			*Regime properties*		
$\alpha(s_t=1)$	0.0181*** (0.0003)				
$\beta(s_t=1)$	0.5015*** (0.0309)		n_i	Prob.	Duration
$\alpha(s_t=2)$	0.0088 (0.0188)	Regime 1	1041.10	0.750	7.770
$\beta(s_t=2)$	0.1817*** (0.0229)	Regime 2	347.90	0.250	2.590

	MS DCC GARCH	DCC GARCH		*Transition probabilities*	
log L	-18066.806	-20075.983			
AIC	26.075	28.936		Regime 1	Regime 2
HQ	26.134	28.964	Regime 1	0.871	0.387
BIC	26.233	29.011	Regime 2	0.129	0.614

LR linearity test 4018.3546*** (0.0000) [0.0000]

Note: The table reports the estimates of the MS-DCC-GARCH model given in Equations (1)-(3). The GARCH part of the model is specified as a GARCH(1,1). The models are estimated over the full sample period 12/1/2009-12/5/2014 with n=1390 observations. See the notes to Table 3 for the explanation of the parameters and statistical tests.

the EAU and CER markets, in views of the standard LR p-values and Davies (1987) upper bound for the *p-values* much below 1% in both cases.

3.2.2. Volatility spillovers to EUA and CER carbon markets

Table 3 reports the parameter estimates of the MS-DCC-GARCH model for the EUA market. We observe that the volatility spillover parameters ($a_{i,j}$,$b_{i,j}$) relating to Equation (2) are generally highly significant, implying significant risk transmission across the energy prices and the EUA carbon spot and futures prices. As expected, the volatility spillovers are strong and positive between the spot (EUAS) and futures (EUAF) markets. Similarly, strong volatility transmission from the electricity market to EUA spot and futures markets is observed without significant effect in the opposite direction. The finding of a significant electricity market effect on the carbon price is consistent with Keppler and Mansanet-Bataller (2010) and Sousa and Aguiar-Conraria (2014). There is also significant volatility transmission from coal and natural gas prices to electricity price. Those primary energy sources are used in electricity generation, while oil is not.

In the case of the CER market, the findings reported in Table 4 do not yield as significant spillover effects as we observed for the EUA market. The weaker volatility spillovers to the CER spot and futures markets can be due to several important market characteristics, potentially leading to the segmentation of the CER market from primary energy commodities as well as the EUA market. The EUA is the underlying security in the EU ETS cap-and-trade program and is the most commonly traded carbon credit globally, making up more than 80% of the global market volume (Mizrach, 2012). To that end, the EUAs play a leading role in spot price formation. On the other hand, the CDM fashioned by the Kyoto Protocol, affords incentives for developing countries to reduce their carbon emissions. These projects produce CER credits which are substitutable for permits in the EU ETS. The CER credits are also affected by project certification concerns. In fact, the cointegration test carried out by Mizrach suggests that there are no common factors between the EUA and secondary CER prices, implying two independent trends. This suggests that CER credits are still driven by CDM specific factors. In sum, the long-term nature of the CER contracts under the Clean Development Mechanism (CDM) and the CDM driven nature of CERs imply certain independence from the EUA and energy markets.[10]

Despite the weaker spillover effects observed for the CER market, the findings suggest significant volatility persistence in this market.The volatility persistence coefficients measured by $a_{ii} + b_{ii}$ in the GARCH specification are respectively 0.41, 1.08, 0.36, 0.98, and 1.06 for the CER

[10] Under the Kyoto Protocol, the CDM is a project-based financing mechanism whereby eligible Annex 1 Parties may purchase carbon credits generated by projects hosted in developing non-Annex 1 countries.

futures, CER spot, electricity futures, natural gas futures, and coal futures variables in the CER market model. They are respectively 0.54, 0.40, 0.77, 0.96, and 0.96 for the EUA futures, EUA spot, electricity, natural gas, and coal variables in the EUA market model. These findings indicate strong volatility persistence for CER spot, coal and natural gas futures contracts, with likely permanent memory for CER spot and coal in the CER model. We observe moderate volatility persistence for EUA spot and futures and electricity in the EUA market model and for the CER futures and electricity in the CER market model, suggesting different volatility dynamics.

Table 5 presents formal volatility spillover tests for the EUA and CER markets, which are based on Wald tests involving two zero restrictions on the relevant elements of matrices A and B. For example, the null hypothesis of no volatility spillover from the electricity returns to the EUA or CER futures returns is tested by imposing the restriction $a_{13} = b_{13} = 0$. The test results reported in Table 5 strongly reject the no volatility spillover hypothesis with the exception of volatility spillover from coal to CER futures. This confirms the presence of extensive volatility spillovers from energy prices to the EUA and CER markets.

Table 5. Volatility spillover tests

H_0: No volatility spillover from row variable to column variable

	EUAF	EUAS		CERF	CERS
EUAS	299.7072***	--	CERS	7.0168**	--
EUAF	--	633.8713***	CERF	--	1750.7370***
ELECTRIC	31.2979***	28.6637***	ELECTRIC	530.2529***	10.8706***
GAS	11.1154***	13.3312***	GAS	18.4174***	43.9574***
COAL	19.8579**	32.6166***	COAL	0.8261	330.0446***

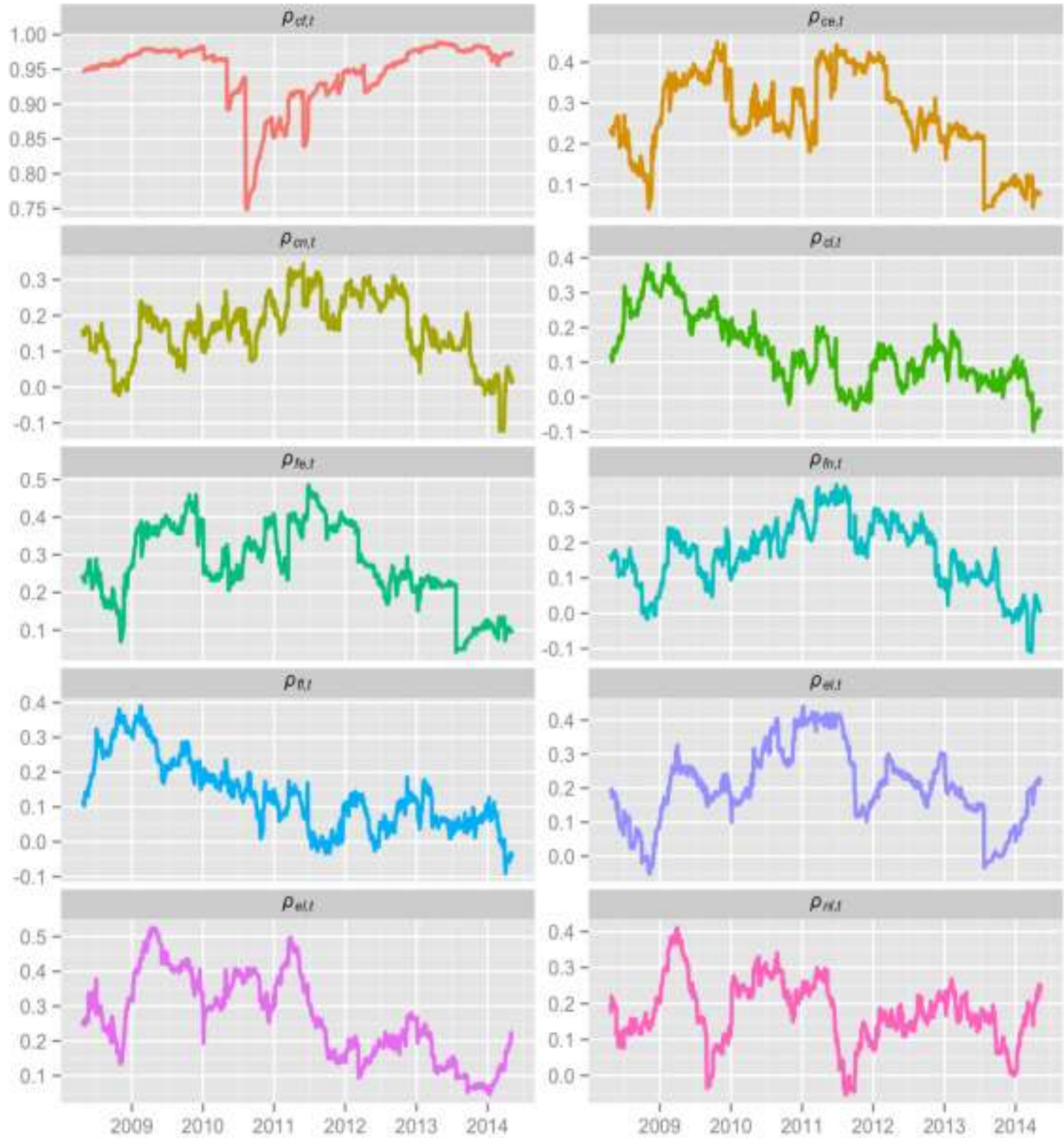
Note: The table reports the Wald tests for testing the no volatility spillover restrictions imposed on Equation (1). The tests report no volatility spillover from the variable in the row to the variable in the column. The tests are distributed as Chi-square with 2 degrees of freedom. ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

3.2.3. Dynamic correlations across market regimes

As explained earlier, the parameters $\alpha(s_t)$ and $\beta(s_t)$, $s_t \in \{1, 2\}$, in Tables 3-4 generate regime-specific conditional correlations in the MS-DCC-GARCH model. For both EUA and CER market models, $\alpha(s_t)$ and $\beta(s_t)$ are highly significant in both regime 1 (low volatility) and regime 2 (high volatility). Therefore, there are significant correlations among the series in both regimes. The smoothed regime probabilities plotted in Figure 4 confirm this empirical finding. However, since the estimates for $\alpha(s_t)+\beta(s_t)$ across the regimes are quite different, the low and high volatility regimes are characterized by very different dynamic correlation structures. Indeed, the sums $\alpha(s_t)+\beta(s_t)$ are 0.78 (0.59) for the low (high) volatility regime in the EUA market, and 0.52 (0.19) for the low (high) regime in the case of the CER market. Since these parameters control for the correlation persistence implied by the models, the findings suggest that the correlations are more persistent in the low volatility regimes than in the high volatility regimes in both markets. Moreover, higher values of $\alpha(s_t)+\beta(s_t)$ for the EUA market compared to the CER market in both regimes imply that the correlation persistence is more pronounced in the EUA market.

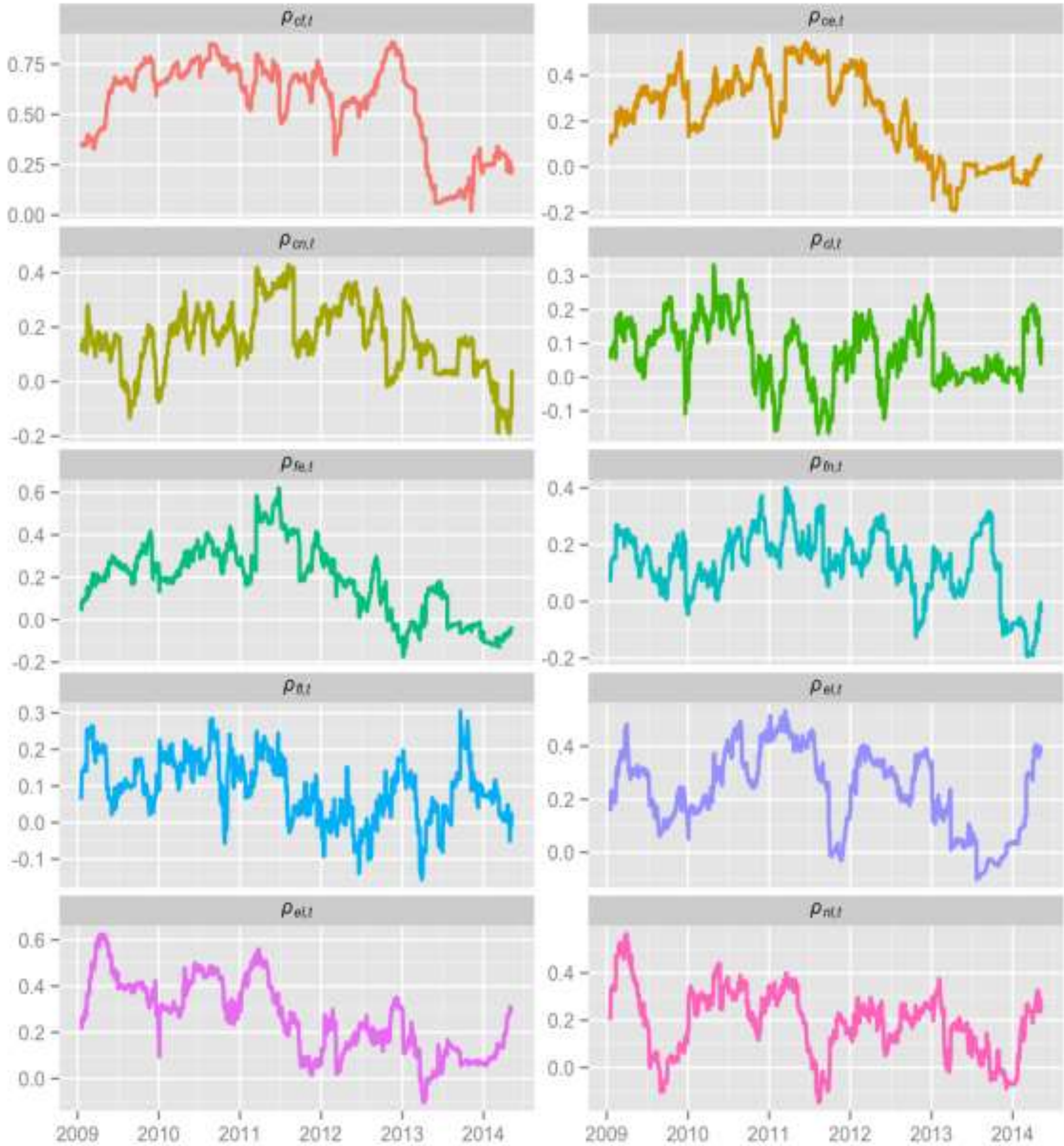
The features of correlation persistence are indeed reflected in the dynamic correlations plotted in Figures 2 and 3 for the EUA and CER market models, respectively. The correlation estimates plotted in Figure 2 for the EUA market are on average greater than those for the CER market in Figure 3, which supports the implications of the $\alpha(s_t)$ and $\beta(s_t)$. The persistence and regime properties of the EUA and CER markets as captured by differences in the estimates of the $\alpha(s_t)$ and $\beta(s_t)$ parameters do show similar analogous features also in terms of transition probabilities, ergodic (regime) probabilities, and duration of the regimes. In Tables 3 and 4, the transition probability estimates p_{11} (p_{22}) are 0.922 and 0.871 (0.428 and 0.614) for the EUA and the CER markets, respectively. Thus, the low volatility regime is more persistent for the EUA market than for the CER market, while the high volatility regime is less persistent. Regime persistence differences are also reflected in the transition probability estimate from the high (low) volatility regime (p_{12}) to the low (high) volatility regime (p_{21}). We typically see that the carbon markets spend much of the time in the low volatility regime, resulting in higher duration estimates

Figure 2. Dynamic correlation estimates from the MS-DCC-GARCH model for the EUA market model



Note: Figure plots the dynamic correlation estimates from the MS-DCC-GARCH model given in Equations (1)-(3). The symbol $\rho_{ij,t}$ stands for the dynamic correlation between the series *i* and *j* at time *t*, $i,j \in \{c,f,e,n,l\}$, where *c* stands for the EUA spot price, *f* stands for the EUA futures price, *e* stands for the electricity price, *n* stands for the natural gas price, and *l* stands for the coal price.

Figure 3. Dynamic correlation estimates from the MS-DCC-GARCH model for the CER market model

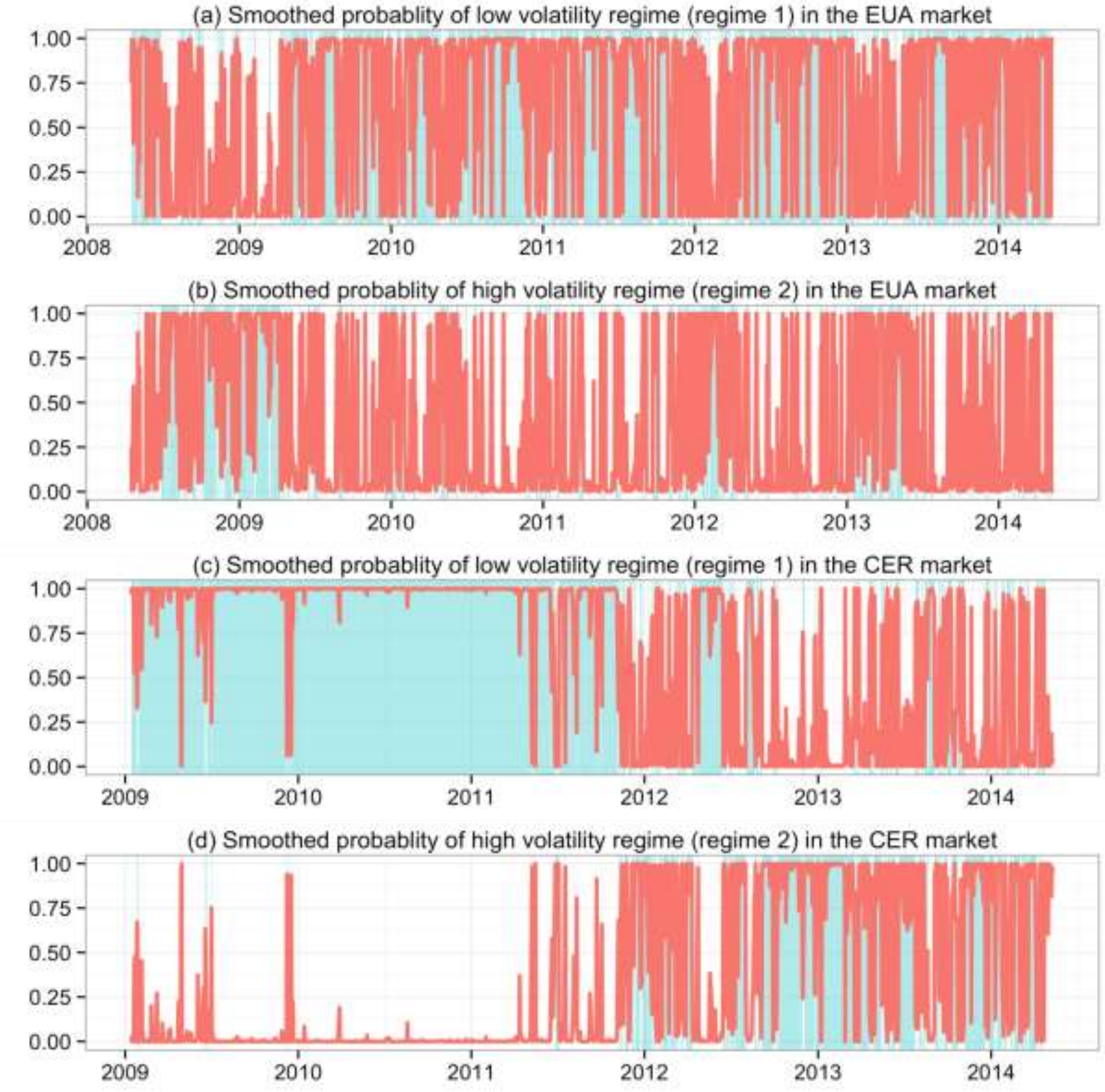


Note: See notes to Figure 2 for the definition of the variables.

for the low volatility regime compared to the high volatility regime. The durations of the low volatility regimes are 12.770 days and 7.770 days while the durations of the high volatility regimes are 1.750 days and 2.590 days, respectively, for the EUA and CER markets.

Another noteworthy feature of the dynamic correlation estimates in Figures 2 and 3 are their highly time-varying nature, providing support for the DCC specification against a constant correlation specification. In general, correlation values tend to decline after mid-2011 which also coincides with the end of the euro-zone crisis. We also note a significant structural break in the correlations between EUA spot and futures in mid-2010, which seems to happen long after Phase I ended in 2008, and another break near the end of Phase II in 2012.

Figure 4. Smoothed probability estimates



Note: The figure plots the smoothed probability estimates of the low volatility regime (regime 1) and the high volatility regime (regime 2). The shaded regions in the figures correspond to the periods where the smoothed probability of the corresponding regime is the maximum.

The smoothed probability estimates plotted in Figure 4 also reveal significant features in both the EUA and CER markets. As indicated earlier, there is a lack of competitive conditions and there are regulatory changes regarding both markets. On the other hand, there are access constraints on the use and the availability of CERs, caps on the amount of CERs, and uncertainty surrounding the CERs. The results show that the low volatility regime for the CER market corresponds to pre-2012 period which is the end of Phase II. Periods after mid-2012 are almost uniformly periods of high volatility for the CER market. This period corresponds to Phase III (the post Kyoto phase) which started in 2012 and changed a number of rules regarding the carbon market. In the CER market, 75% percent of the observations fall into the low volatility regime, while 25% fall into the high volatility regime. On the other hand, the EUA market can mostly be characterized by low volatility regime periods with 88% of the observations falling into the low volatility regime. In sum, the periods of high volatility in the EUA market correspond to the initial months of Phase II and Phase III, whereas the high volatility for the CER market mainly corresponds to the post Kyoto period (Phase III).

4. In-sample and out-of-sample hedging performance

4.1. Full sample hedging performance analysis

We obtain regime independent moments and perform in- and out-of-sample analysis of the hedging strategies as in Lee (2010) and Chang et al. (2011). As indicated earlier, we evaluate the portfolios based on three criteria: (i) the optimal hedge ratio; (ii) the optimal portfolio weight; and (iii) the hedge effectiveness index.[11] In-sample portfolios are constructed by first estimating the EUA market model over the sample period 4/15/2008-3/18/2013 and the CER market model over the sample period 12/1/2009-3/18/2013, and then computing the in-sample covariance matrix (P_t) in Equation (3). The in-sample analysis contains 1,285 (1,090) portfolio points for the EUA (CER) market. On the other hand, the out-of-sample portfolios are constructed following a recursive

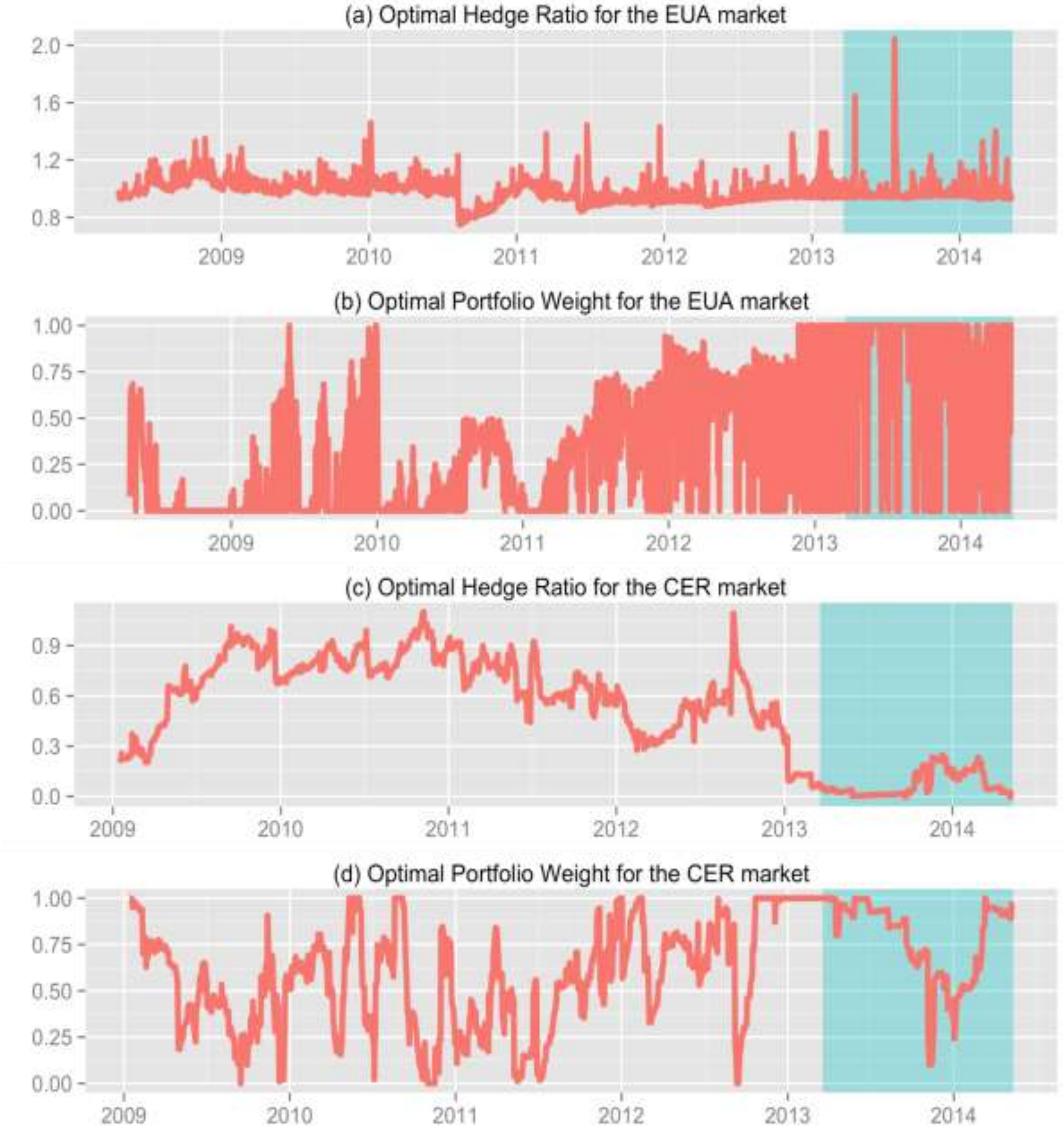
[11] The optimal hedge ratio is defined as $\theta_t^* = h_{cf,t} / h_{f,t}$, where $h_{f,t} = var(R_{f,t})$ and $h_{cf,t} = cov(R_{c,t}, R_{f,t})$ estimated by Equations (1)-(3). The regime independent covariances are obtained as the probability weighted average of regime-dependent covariances where the weights are corresponding predictive regime probabilities. See Kroner and Ng (1998), Hammoudeh et al. (2010), and Chang et al. (2011) for details regarding the optimal weight calculations. The covariance term is obtained as in optimal hedge ratio. As to the hedging effectiveness, it was originally proposed by Ederington (1979) and measures the percentage reduction in the variance of the hedged portfolio relative to the unhedged portfolio.

procedure. The in-sample estimates of the EUA and CER market models are firstly used to obtain the predicted covariance matrix P_{T+1} and to construct the first out-of-sample portfolio for 3/19/2013. Portfolio holdings are then adjusted recursively on a daily basis by adding the next observation and updating the predicted covariance matrix for the next day. By doing so, we obtain 300 out-of-sample portfolio points over the period 3/19/2013-12/5/2014. Finally, hedged and optimal portfolios are computed.

The need for a dynamic hedging strategy is warranted by significant time variation in the correlations across the carbon markets. In addition, the finding of significant correlations between carbon and energy markets implies that the factors impacting the energy markets also drive volatility in the emission markets. Considering possible drivers of volatility in energy prices such as demand and supply side factors, weather conditions, climate change, and economic growth trends, it can be argued that commonalities in energy market fundamentals also impact CO_2 trade. Furthermore, significant volatility transmissions from energy markets to the market for carbon emissions further emphasize the need for hedging.

Figure 5 presents evidence of significant time variation in the hedge ratios and optimal portfolio weights for both the EUA and CER markets with the CER market exhibiting greater volatility in the optimal hedge positions. A close look at the in-sample statistics for the unhedged and hedged portfolios reported in Table 6 indicates significant gains from adopting dynamic hedging strategies, particularly for the EUA market. As expected, the minimum-variance hedging strategy yields the greatest reduction in the volatility of the hedge portfolio, with 92% (71%) variance reduction achieved by the dynamic (static) strategies in the EUA market. Similarly, the minimum-variance hedging strategy yields 40% (38%) reduction in variance with the dynamic (static) strategies in the case of the CER market. It is clear that the dynamic hedging strategy yields the largest benefit for the EUA market. On the other hand, we find that the optimal portfolio

Figure 5. In-sample and out-of-sample estimates of the optimal hedge ratio and optimal portfolio weight



Note: Figure plots the estimates of the time-varying optimal hedge ratios and optimal portfolio weights. The shaded regions in the graphs correspond to the out-of-sample period.

approach yields much inferior results both with respect to portfolio return and risk compared to the minimum-variance hedging strategy.

A comparison of the hedging performances for EUA and CER futures, presented in Panels A and B in Table 6 respectively, suggests that hedging does not work as effectively in the CER market as in the case of the EUA market. It is important to note that the EUAs are the most commonly traded type of carbon allowance globally, accounting for more than 80% of the global

Table 6. Summary statistics for in-sample hedge portfolios

	Mean	S.D.	Min	Max	HE
Panel A: EUA Market					
Unhedged Portfolio Return	-0.147	2.946	-15.876	24.154	--
MS-DCC-GARCH Hedged Portfolio Return	-0.003	0.780	-10.334	9.691	92.995
DCC-GARCH Hedged Portfolio Return	-0.020	1.572	-9.733	9.567	71.508
MS-DCC-GARCH Optimal Portfolio Return	-0.144	2.830	-15.097	21.846	7.687
DCC-GARCH Optimal Portfolio Return	-0.146	2.865	-15.876	23.814	5.418
MS-DCC-GARCH Optimal Hedge Ratio	1.004	0.067	0.240	1.392	--
DCC-GARCH Optimal Hedge Ratio	0.387	0.433	0.001	2.288	--
MS-DCC-GARCH Optimal Portfolio Weight	0.189	0.248	0.000	1.000	--
DCC-GARCH Optimal Portfolio Weight	0.387	0.179	0.000	1.000	--
Panel B: CER Market					
Unhedged Portfolio Return	-0.337	4.014	-33.647	17.693	--
MS-DCC-GARCH Hedged Portfolio Return	-0.145	3.107	-29.605	18.072	40.090
DCC-GARCH Hedged Portfolio Return	-0.157	3.150	-24.587	19.058	38.411
MS-DCC-GARCH Optimal Portfolio Return	-0.338	3.735	-33.642	15.397	13.423
DCC-GARCH Optimal Portfolio Return	-0.331	3.741	-33.647	17.693	13.129
MS-DCC-GARCH Optimal Hedge Ratio	0.638	0.228	0.054	1.101	--
DCC-GARCH Optimal Hedge Ratio	0.489	0.190	0.126	1.635	--
MS-DCC-GARCH Optimal Portfolio Weight	0.575	0.288	0.000	1.000	--
DCC-GARCH Optimal Portfolio Weight	0.619	0.253	0.000	1.000	--

Note: The in-sample period for the EUA market covers 4/15/2008-3/18/2013 with 1285 observations and for the CER market it covers the period 12/1/2009-3/18/2013 with 1090 observations. HE stands for the hedge effectiveness index.

trading volume. Thus, it can be argued that the greater liquidity and tradability associated with these contracts works to enhance their hedging effectiveness. In contrast, the CER contacts lack this characteristic. Unlike EUAs, the CER credits are affected by project certification concerns as the type of projects that are qualified for CDM credits has often been challenged. Consequently, policy uncertainties surrounding CERs have thus reduced its hedging performance. Furthermore, as discussed in Section 3.2.3 and later in Section 4.2, the dynamic correlation estimates presented in Figures 2 and 3 indicate a dramatic fall in spot-futures correlations particularly in the case of the CER market. The lower correlations between CER spot and futures returns further hurt the hedging performance of these contracts as correlations have a direct impact on the performance of future contracts in hedging strategies.

Similar findings are observed in the case of the out-of-sample results presented in Panels A and B in Table 7 for the EUA and CER markets, respectively. Although the minimum-variance strategy is found to yield the greatest risk reduction in the EUA market, we observe that the optimal portfolio approach yields greater HE index values for the CER market than the minimum-variance strategy. In either case, however, the dynamic strategy yields significantly better results than the static alternative.

Table 7. Summary statistics for the out-of-sample hedge portfolios

	Mean	S.D.	Min	Max	HE
Panel A: EUA Market					
Unhedged Portfolio Return	0.111	5.375	-43.000	28.701	--
MS-DCC-GARCH Hedged Portfolio Return	-0.012	2.280	-28.246	24.858	82.000
DCC-GARCH Hedged Portfolio Return	0.133	2.798	-29.256	19.741	72.897
MS-DCC-GARCH Optimal Portfolio Return	0.109	4.778	-41.709	19.311	20.966
DCC-GARCH Optimal Portfolio Return	0.107	4.810	-42.459	19.666	19.916
MS-DCC-GARCH Optimal Hedge Ratio	1.005	0.293	0.765	4.467	--
DCC-GARCH Optimal Hedge Ratio	0.418	0.949	0.001	10.416	--
MS-DCC-GARCH Optimal Portfolio Weight	0.435	0.285	0.000	1.000	--
DCC-GARCH Optimal Portfolio Weight	0.390	0.170	0.000	1.000	--
Panel B: CER Market					
Unhedged Portfolio Return	-0.290	11.868	-76.913	99.040	--
MS-DCC-GARCH Hedged Portfolio Return	-0.231	11.716	-75.178	99.040	2.531
DCC-GARCH Hedged Portfolio Return	-0.167	11.943	-74.178	99.040	-1.266
MS-DCC-GARCH Optimal Portfolio Return	-0.266	9.997	-69.315	71.236	29.041
DCC-GARCH Optimal Portfolio Return	-0.350	8.683	-63.956	53.061	46.470
MS-DCC-GARCH Optimal Hedge Ratio	0.072	0.073	-0.005	0.247	--
DCC-GARCH Optimal Hedge Ratio	0.266	0.141	0.073	0.944	--
MS-DCC-GARCH Optimal Portfolio Weights	0.778	0.217	0.101	1.000	--
DCC-GARCH Optimal Portfolio Weights	0.913	0.196	0.025	1.000	--

Note: The out-of-sample period for the EUA market covers the period 3/19/2013-12/5/2014 with 300 observations, and for the CER market it covers the period 3/19/2013-12/5/2014 with 300 observations.

Despite the reduction of risk documented for both the EUA and CER markets, we observe in general that hedging is not generally effective in managing carbon price risks, more so in the case of the CER market. To that end, it must be noted that carbon futures and spot prices are cointegrated. Thus, they make expensive hedges and are not very effective in reducing risk. Furthermore, as the findings from the regime switching model suggest, the dynamic correlation estimates are highly time varying with long periods during which the correlation between spot and futures returns fall below 10%. Consequently, as the futures and spot markets drift away, hedges become less effective. Furthermore, the EU ETS market is relatively new with frictions and plagued with fundamental uncertainties regarding the future of these markets. As noted in a Reuters article, carbon prices have fallen dramatically in recent years partially as a result of the worsening global economic outlook, slowing down the amount of greenhouse gasses pumped into the atmosphere, hence slowing down the demand for carbon contracts.[12] Furthermore, the oversupply of carbon allowances by the U.N. climate panel has led to a glut in emissions permits, resulting in the supply of carbon offsets far outstripping the demand in the market. Therefore, it can be argued that the market downturn experienced particularly at the end of Phase II and recently in Phase III will most likely lead hedges to become less effective. However, as noted in a recent Bloomberg article, this price trend may turn dramatically if carbon trading is advocated as part of the global climate pact in Paris in December, driving a larger number of nations to manage their emissions caps.

4.2. Phase II and Phase III subsample hedge performance analysis

As stated earlier, Phase I (2005 to 2007) of the EU ETS was a trial period and Phase II (2008-2012), i.e. the first commitment period, is associated with stricter caps as a number of industrialized nations have committed themselves to binding emissions targets during this period. .

[12] "Carbon offsets near record low, worst performing commodity," Reuters (Aug. 5, 2011). http://www.reuters.com/article/2011/08/05/us-carbon-low-idUSTRE77442920110805

On the other hand, Phase III (2013-2020), i.e. the second commitment period, has experienced a number of changes including an overall EU cap, tighter limits on the use of offsets, and a move from allowances to auctioning. In order to provide further insight to the evolution of carbon market dynamics and their hedging effectiveness, we analyze the different phases of the EU ETS by dividing the sample period into two subsamples that correspond to the Phase I and II periods. The sample periods for both the EUS and CER markets cover almost all of Phase II and about 17 months into Phase III.

The smoothed probability estimates presented in Figure 4 suggest that the second regime mostly corresponds to Phase III particularly for the CER market. This period has seen a dramatic fall in carbon prices as a result of worsening global economic outlook and an oversupply of carbon allowances, driving CER prices almost to zero in recent years. On the other hand, we observe somewhat mixed results in the case of the EUA market although the second regime is generally found to correspond to transition periods from across the different phases in early 2009 and later in 2012. Similarly, the dynamic correlation estimates presented in Figures 2 and 3 exhibit markedly different patterns over the Phase II and Phase III sub-periods. We observe the correlations between carbon spot and futures returns fall dramatically for the CER market, from around 0.75 to 0.25. In the case of the EUA market, the correlations between the spot and futures returns are significantly lower during the 2010-2013 period, while significantly higher correlations are observed during the post-Phase II period. The dynamic correlation estimates indicate that the hedge performance might vary greatly across the different phases of the EU ETS, thus validating the motivation for the sub-period analysis. For this purpose, we re-estimate the models for the two sub-periods corresponding to the Phase II and Phase III periods and compare the in-sample hedge performance across the two phases.

Table 8: Summary Statistics for the Phase II and Phase III Subsample Hedge Portfolios for the EUA Market

	Mean	S.D.	Min	Max	HE
Panel A: Phase II Subsample (Apr. 16, 2008-Dec. 31, 2012)					
Unhedged Portfolio Return	-0.110	2.570	-10.348	18.960	--
MS-DCC-GARCH Hedged Portfolio Return	-0.007	0.691	-10.334	5.556	92.770
DCC-GARCH Hedged Portfolio Return	-0.011	1.420	-9.733	5.624	69.462
MS-DCC-GARCH Optimal Portfolio Return	-0.102	2.466	-9.529	18.133	7.857
DCC-GARCH Optimal Portfolio Return	-0.103	2.495	-9.660	18.493	5.725
MS-DCC-GARCH Optimal Hedge Ratio	1.011	0.072	0.240	1.392	--
DCC-GARCH Optimal Hedge Ratio	0.402	0.435	0.001	2.288	--
MS-DCC-GARCH Optimal Portfolio Weight	0.150	0.220	0.000	1.000	--
DCC-GARCH Optimal Portfolio Weight	0.382	0.183	0.000	0.700	--
Panel B: Phase III Subsample (Jan. 1, 2013-May 12, 2014)					
Unhedged Portfolio Return	-0.174	5.296	-43.000	28.701	--
MS-DCC-GARCH Hedged Portfolio Return	-0.012	2.176	-28.246	24.858	83.124
DCC-GARCH Hedged Portfolio Return	-0.011	2.706	-29.256	19.741	73.894
MS-DCC-GARCH Optimal Portfolio Return	-0.183	4.736	-41.709	21.846	20.028
DCC-GARCH Optimal Portfolio Return	-0.185	4.793	-42.459	23.814	18.092
MS-DCC-GARCH Optimal Hedge Ratio	0.998	0.260	0.765	4.467	--
DCC-GARCH Optimal Hedge Ratio	0.443	0.870	0.001	10.416	--
MS-DCC-GARCH Optimal Portfolio Weights	0.391	0.300	0.000	1.000	--
DCC-GARCH Optimal Portfolio Weights	0.378	0.177	0.000	0.521	--

Note. The table reports the summary statistics for the in-sample EUA market hedge portfolios corresponding to Phase II and Phase III of the EU ETS. The hedge portfolio corresponding to the Phase II and Phase III includes 1,034 and 355 observations, respectively.

Panels A and B in Table 8 present the summary statistics for the hedge portfolios for the EUA market, for Phase II and Phase III sub-periods, respectively. For the EUA market, Phase II covers Apr. 16, 2008-Dec. 31, 2012 while Phase III corresponds to Jan. 1, 2013-May 12, 2014. Consistent with the findings for the full sample, we observe that the MS-DCC-GARCH model provides the best hedge performance among all models, consistent across both sup-periods. We also observe that the hedge effectiveness is generally better during Phase II, most likely due to the weaker correlations between the spot and futures markets during the initial stages of the Phase III. Panels A and B in Table 9 presents the findings for the CER market. Once again, we observe that The MS-DCC-GARCH model outperforms all other models in terms of the hedge effectiveness, consistent across both sub-periods. Interestingly, while the in-sample hedge performance of CER futures during Phase II is better than the full sample hedge effectiveness values (Table 6), we observe that CER futures do not work as well during Phase. The lower hedge effectiveness for the CER market during Phase III may be attributed to weaker correlations between the spot and futures markets. Overall, the sub-period analysis suggests significant structural changes in dynamic correlations and hence the effectiveness of hedges during the different phase of EU ETS.

5. Conclusion

This study uses a Markov regime-switching dynamic correlation, generalized autoregressive conditional heteroscedasticity (MS-DCC-GARCH) model to examine the volatility spillovers between four primary energy futures prices and Europe-based carbon futures contracts in the EUA and CER markets, while accounting for time variations and structural breaks in the spillovers. It also evaluates the optimal hedge ratios, dynamic hedging strategies and hedging effectiveness in both carbon markets based on the derived regime dependent and regime independent optimal hedge ratios. The study also examines the subsamples corresponding to Phase II and Phase III of the EU ETS.

The results show that the carbon emission markets are linked to changes in the electricity, natural gas and coal futures markets, and more significantly so in the case of the EUA market. The link is formed through the effects of the forces that drive volatility in the energy market as well as time-varying risk transmissions from these energy markets to the carbon market, both in terms of the cross-market correlations and volatility spillovers. The evidence of risk transmission to carbon markets suggests the need for sound policies to stabilize the carbon markets as well as good instruments to effectively hedge the positions. Instability in the carbon market coupled with inability to hedge positions may generate significant risk exposures and unexpected failures due to changing links between the carbon spot and futures markets, and between CO_2 emission prices and energy prices. Policymakers should advocate hedging policies that help improve the cost effectiveness of the substitutable EUA and CER CO_2 emission futures markets. In the absence of hedging instruments, these volatile markets are highly risky. Hedging in the short run will also give the polluters time to gradually recourse to cleaner energy sources, with the resulting outcome of lower carbon emissions.

Policymakers and traders should be aware that hedging strategies work differently for the EUA and CER carbon markets. The minimum-variance hedging strategy works better for the EUA market, while the optimal portfolio approach gives better hedging results for the more volatile CER markets. Overall, the hedging strategies are more effective in the EUA market than in the CER market. By considering both in-sample and out-of-sample analysis of comovements and hedging strategies for both EUA and CER markets, we show that the spot and futures segments of these markets exhibit time-varying correlations and hedging effectiveness. This hedging effectiveness is however found to be highly volatile, particularly in the CER market possibly due to its dependence on the CDM projects. We also find that CO_2 futures are not always highly effective as hedge instruments because of occasional breaks and shifts in the carbon spot-futures price links.

This result has implications for the adoption of cleaner energy sources in the long run. Another important fact is that the EUA carbon market is subject to volatility spillovers from energy futures markets (electricity, natural gas and coal), with the electricity market being the main volatility transmitter. The volatility spillover from the energy markets to the CER market is weaker than in the case of the EUA market. Our findings finally point to the importance of regime switching in regard of hedging performance, and suggest that ignoring regime switching in the carbon market may result in significant reduction in hedging performance.

Adding the CER market to that of EUA broadens the scope of the carbon trading institutionalized by EU ETS since those products are substitutes and give investors and regulators more opportunities to achieve the objectives. However, this subject is ambitious and will be delegated to a future project.

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