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# 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. These results have important investment and policy implications.

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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 (CER), and the Joint

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[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).

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 as 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. Methods

### 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 $(5 \times 1)$ 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

$$R_t = \Phi_0 + \sum_{i=1}^{p} \Phi_i R_{t-i} + \varepsilon_t$$
$$\varepsilon_t = D_t z_t$$

(1)

where $D_t = \text{diag}(h_{c,t}^{1/2}, h_{f,t}^{1/2}, h_{e,t}^{1/2}, h_{n,t}^{1/2}, h_{l,t}^{1/2})$ 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 $(5 \times 5)$ parameter matrices $\Phi_i$, $i = 1, 2, ..., p$. The unexplained component $\varepsilon_t$ follows a GARCH specification described as $\varepsilon_t | \psi_{t-1} \sim ID(0, P_t)$ 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

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

(2)

where $c$ is a $(5 \times 1)$ vector of constants, $A$ and $B$ are $(5 \times 5)$ 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 correla-

tions to vary over time by specifying the variance-covariance matrix $P_t = D_t \Gamma_t D_t$ with $\Gamma_t$ 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 $\Gamma_t = \text{diag}\{Q_t\}^{-1/2} Q_t \text{diag}\{Q_t\}^{-1/2}$. 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

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

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 $\sum_{i=1}^{2} p_{ij} = 1$ .

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[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 Results

### 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

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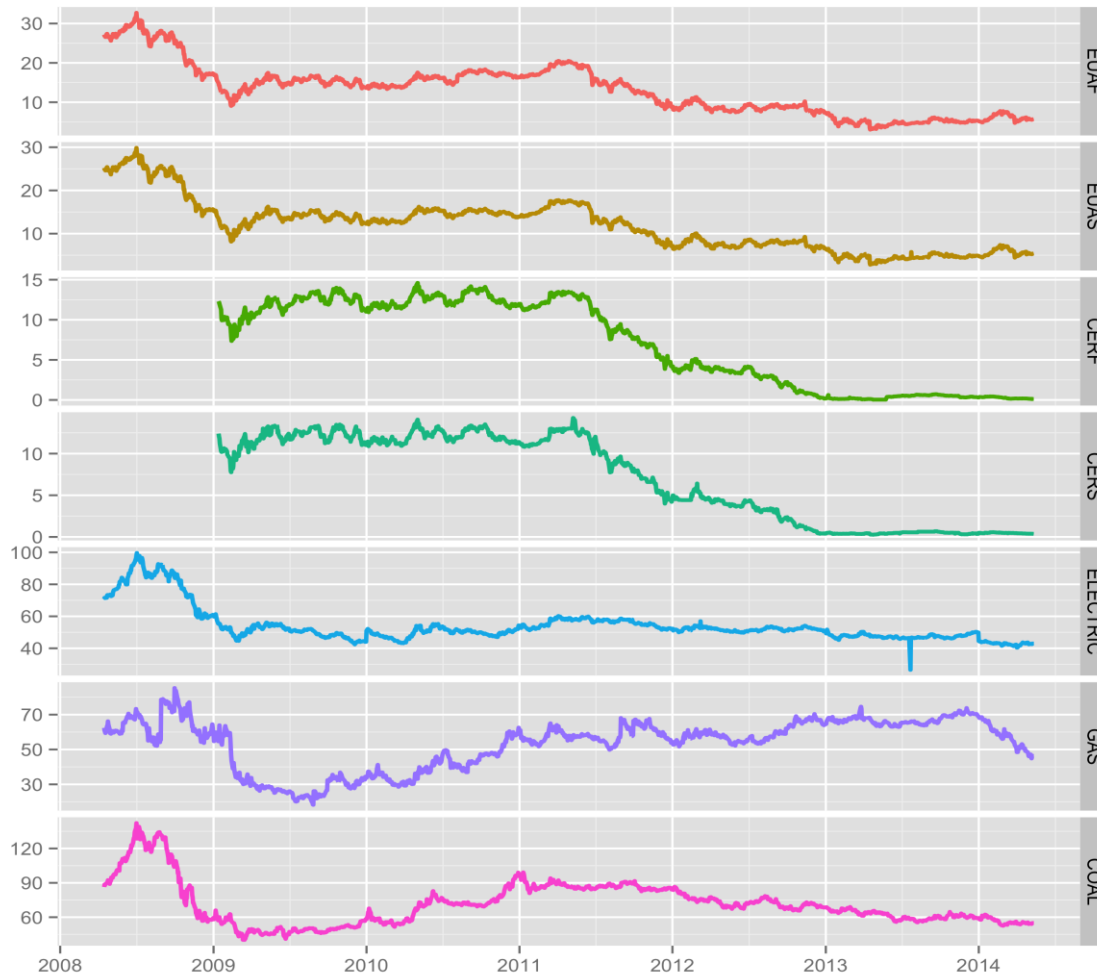


Figure 1 provides the time series plots for the daily futures and spot energy and carbon prices. Not surprisingly, we observe a general negative effect of the 2007-2008 global financial crisis on the energy market, most likely due to the severe economic downturn that prevailed during that period. A similar 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.

**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 |

Notes: This table gives the descriptive statistics for logarithmic returns. 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.

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.

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

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

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.

**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) |

Notes: 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.

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

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 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).

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 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

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[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.

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 potentially be explained by the long-term nature of the CER contracts under the Clean Development Mechanism (CDM), implying certain independence from the EUA and energy markets.[10]

**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 |

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[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.

|  | 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] |
|---|---|

Notes: 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.

On the other hand, 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 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 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 | | | |
|---|---|---|---|---|---|
| $\log L$ | -18066.806 | -20075.983 | | Transition probabilities | |
| 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] | | | | |

Notes: 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.

**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*** |

Notes: 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.

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.

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.

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

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.
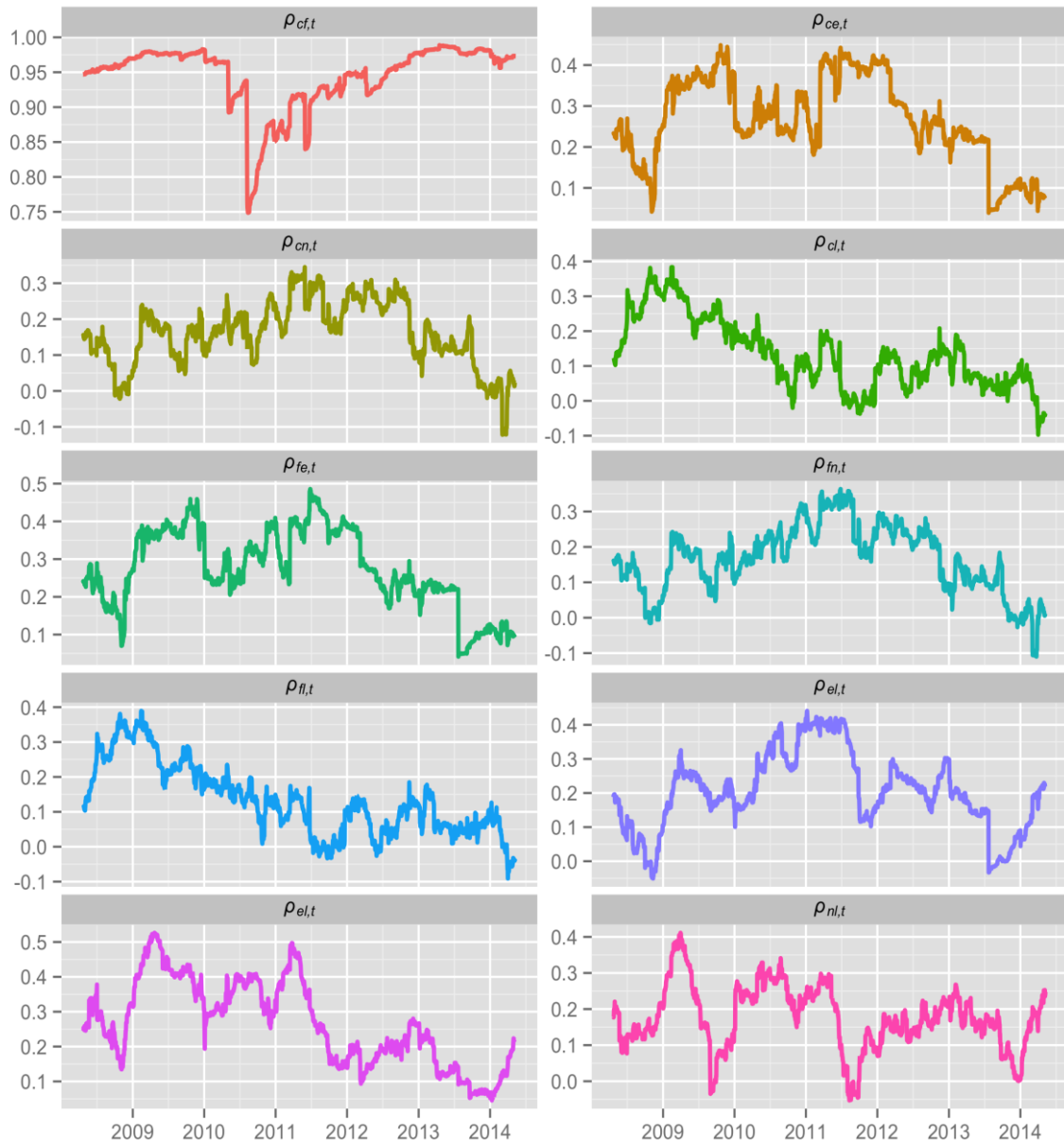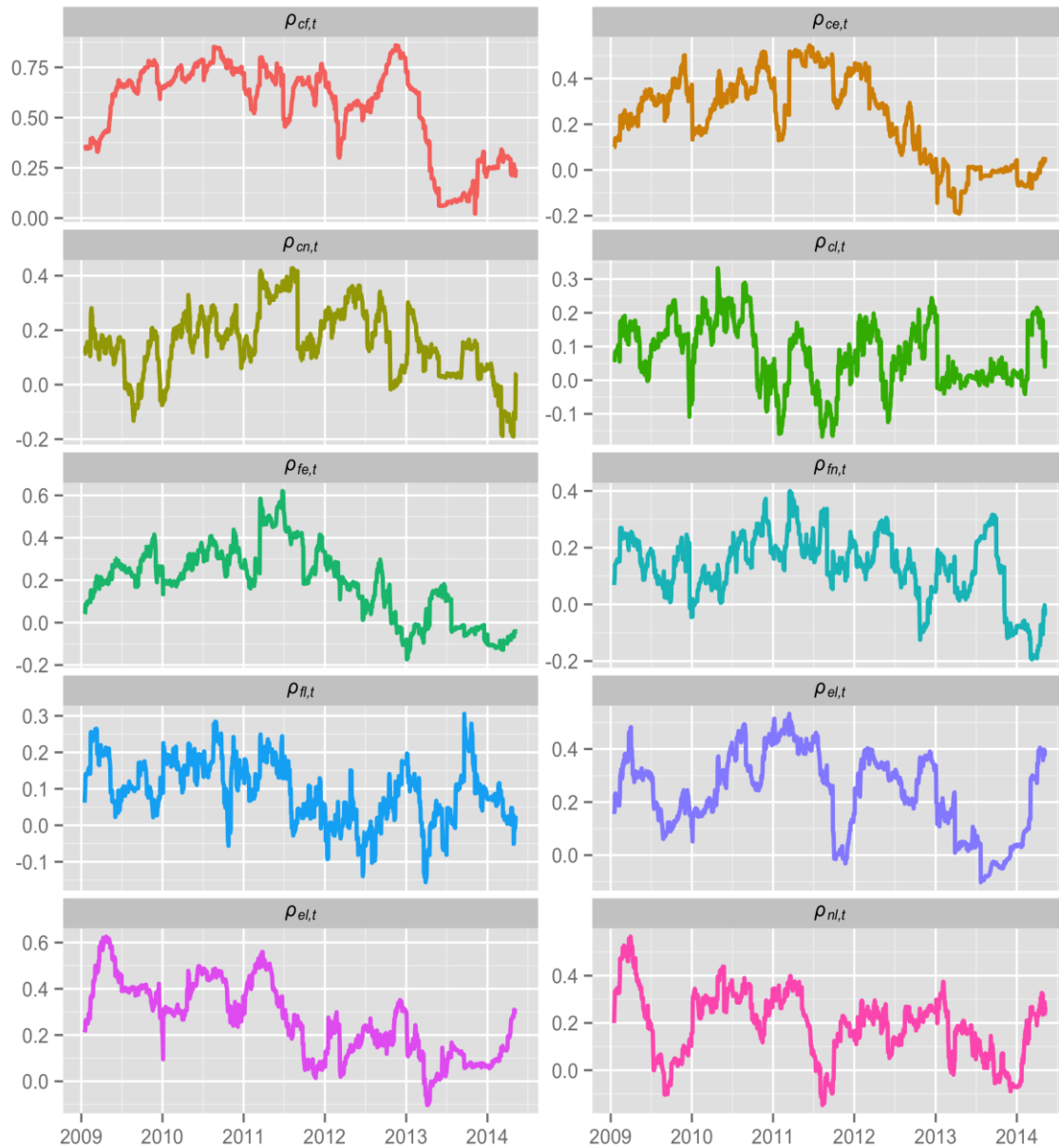
**Figure 3: Dynamic correlation estimates from the MS-DCC-GARCH model for the CER market model**
See notes to Figure 2 for the definition of the variables.



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 proba-

bility 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 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, re-

spectively, 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 correla-

tion specification. In general, correlation values tend to decline after mid-2011 which also coin-

cides with the end of the euro-zone crisis. We also note a significant structural break in the correla-

tions 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.

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).

**Figure 4: Smoothed probability estimates**
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.



(a) Smoothed probablity of low volatility regime (regime 1) in the EUA market



(b) Smoothed probablity of high volatility regime (regime 2) in the EUA market



(c) Smoothed probablity of low volatility regime (regime 1) in the CER market



(d) Smoothed probablity of high volatility regime (regime 2) in the CER market
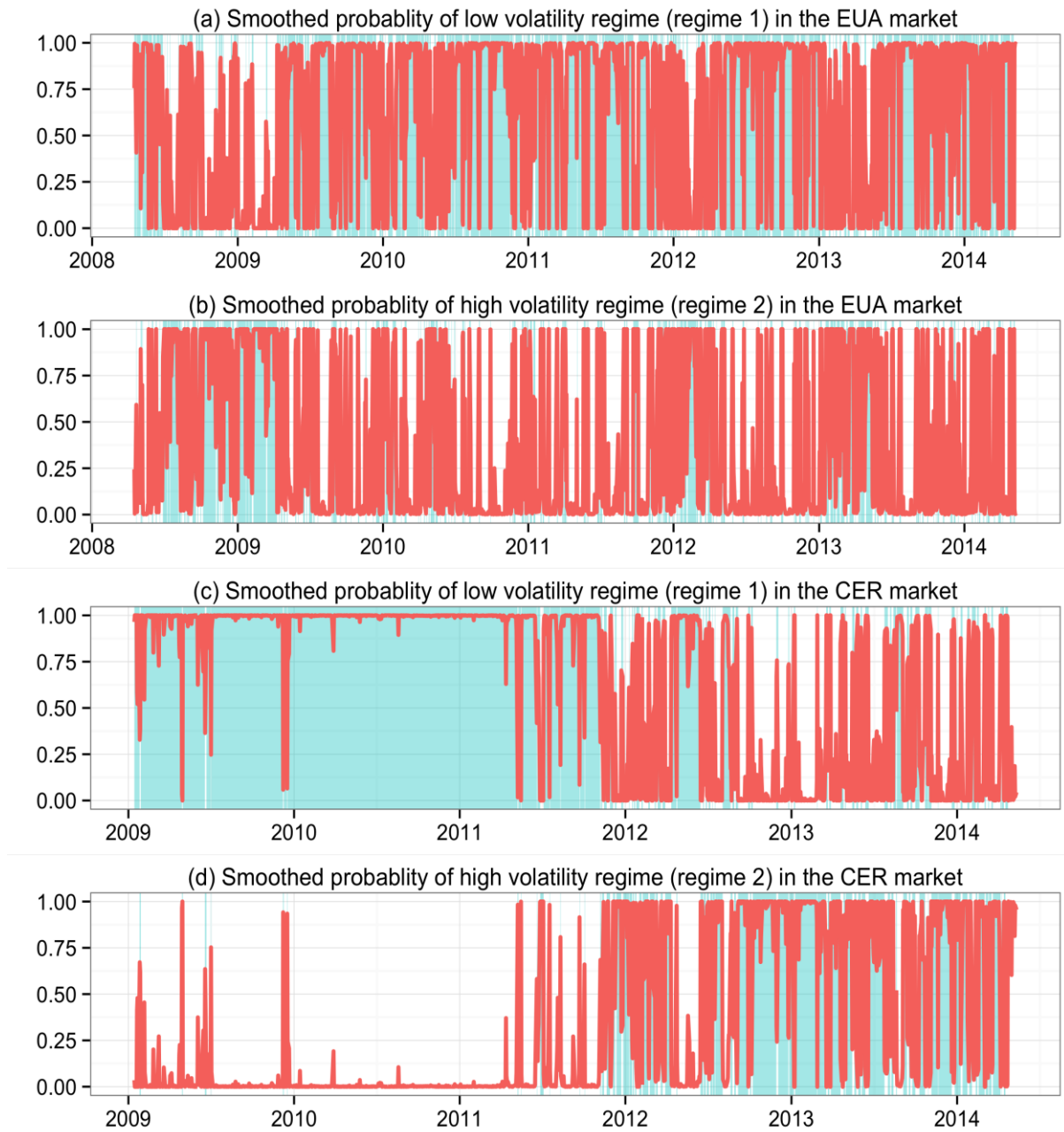
## 4. Discussion: Hedging performance

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 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 implie 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,

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[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.

significant volatility transmissions from energy markets to the market for carbon emissions further

emphasize the need for hedging.

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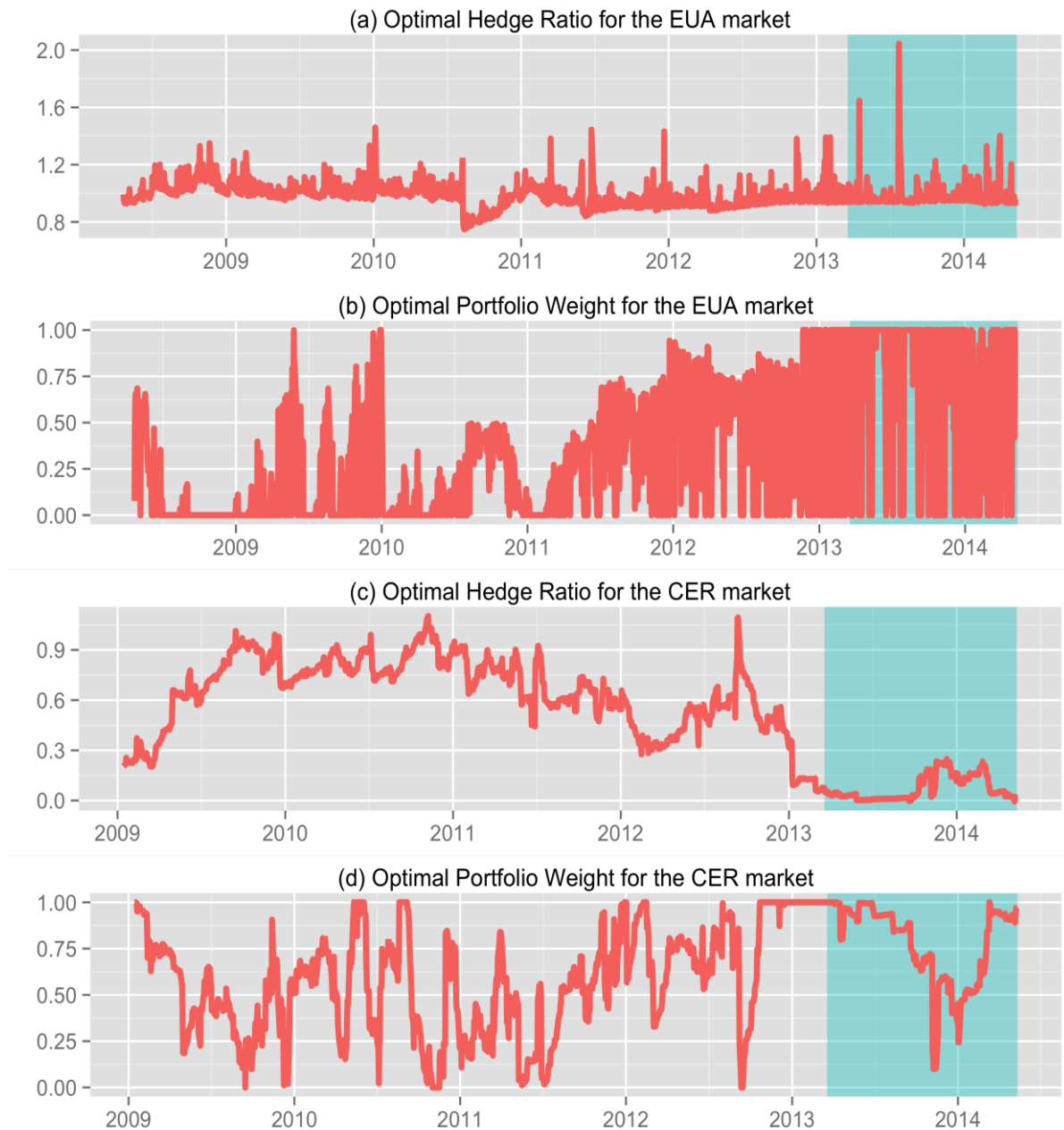


Figure 5 presents evidence of significant time variation in the hedge ratios and optimal port-

folio 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.

**Table 6: Summary statistics for in-sample hedge portfolios**

|  | Mean | S.D. | Min | Max | HE |
|---|---|---|---|---|---|
| *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 | -- |
| | | | | | |
| *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 | -- |

Notes: 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.

On the other hand, we find that the optimal portfolio approach yields much inferior results both with respect to portfolio return and risk compared to the minimum-variance hedging strategy. In the case of the out-of-sample results (Table 7), although the minimum-variance strategy yields 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 better results than the static alternative.

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

|  | Mean | S.D. | Min | Max | HE |
|---|---|---|---|---|---|
| *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 | -- |
| | | | | | |
| *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 | -- |

Notes: 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.

## 5. Conclusions and Policy Implications

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 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.

## References

Aatola, P., Ollikainen, M., Toppinen, A., 2013. Price determination in the EU ETS market: Theory and econometric analysis with market fundamentals. Energy Economics 36, 380-395.

Alberola, E., Chevallier, J., Cheze, B., 2008. Price drivers and structural breaks in European carbon prices 2005-2007. Energy Policy 36, 787–797.

Arouri, M. E. H., Jawadi, F., Nguyen, D. K., 2012. Nonlinearities in carbon spot-futures price relationships during Phase II of the EU ETS. Economic Modelling 29, 884-892.

Billio, M., Caporin, M., 2005. Multivariate Markov switching dynamic conditional correlation GARCH representations for contagion analysis. Statistical Methods & Applications 14, 145–161.

Bredin, D., Muckley, C., 2011. An emerging equilibrium in the EU emissions trading scheme. Energy Economics 33, 353-362.

Cai, J., 1994. A Markov model of switching-regime ARCH. Journal of Business & Economic Statistics 12, 309–316.

Chang, C-L., McAleer, M., Tansuchat, R., 2011. Crude oil hedging strategies using dynamic multivariate GARCH. Energy Economics 33, 912–923.

Creti, A., Jouvet, P.-A., Mignon, V., 2012. Carbon price drivers: Phase I versus Phase II equilibrium? Energy Economics 34, 327-334.

Daskalakis, G., Markellos, R., 2008. Are the European carbon markets efficient? Review of Futures Markets 17, 103-128.

Davies, R. B., 1987. Hypothesis testing when a nuisance parameter is present only under the alternative. Biometrika 74, 33-43.

Ederington, L. H., 1979. The hedging performance of the new futures markets. Journal of Finance 34, 157-170.

Engle, R. F., 2002. Dynamic conditional correlation: a new simple class of multivariate GARCH models. Journal of Business and Economic Statistics 20, 339–350.

Engle, R. F,, Sheppard, K., 2001. Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH. University of California, San Diego, Discussion Paper No. 2001-15, NBER Working Paper No. 8554.

Fan, J. H., Rocan, E., Akimov, A., 2014. Estimation and performance evaluation of optimal hedge ratios in the carbon market of the European Union Emissions Trading Scheme. Australian Journal of Management 39, 73-91.

Gray, S.F., 1996. Modeling the conditional distribution of interest rates as a regime switching process. Journal of Financial Economics 42, 27–62.

Hamilton, J. D., 1990. Analysis of time series subject to changes in regime. Journal of Econometrics 4, 39–70.

Hamilton, J.D., Susmel, R., 1994. Autoregressive conditional heteroscedasticity and changes in regime. Journal of Econometrics 64, 307–333.

Hammoudeh, S., Yuan, Y., McAleer, M., Thompson, M., 2010. Precious metals-exchange rate volatility transmissions and hedging strategies. International Review of Economics and Finance 20, 633-647.

Keppler, J. H., Mansanet-Bataller, M., 2010. Causalities between CO2, electricity, and other energy variables during phase I and phase II of the EU ETS. Energy Policy 38, 3329-3341.

Kim, C., 1994. Dynamic linear models with Markov-switching. Journal of Econometrics 60, 1-22.

Kim, H.S., Koo, W.W., 2010. Factors affecting the carbon allowance market in the US. Energy Policy, 38, 1879-1884.

Kroner, K., Ng, V., 1998. Modeling asymmetric aomovements of asset aeturns. The Review of Financial Studies 11, 817-844.

Kumar, S., Managi, S., Matsuda, A., 2012. Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. Energy Economics 34, 215-226.

Lee, H-T., 2010. Regime switching correlation hedging. Journal of Banking & Finance 34, 2728–2741.

Ling, S., McAleer, M., 2003. Asymptotic theory for a vector ARMA-GARCH model. Econometric Theory 19, 278–308.

Lutz, B.J., Pigorsch, U., Rotfub, W., 2013. Nonlinearity in cap-and-trade systems: The EUA price and its fundamen-tals. Energy Economics 40, 222-232.

Mansanet-Bataller, M., Pardo, A., Valor, H., 2007. $CO_2$ prices, energy and weather. Energy Journal 28, 73-92.

Milunovich, G., Joyeux, R., 2010. Market efficiency and price discovery in the EU carbon futures. Applied Financial Economics 20, 803-809.

Nazifi, F., 2013. Modelling the price spread between EUA and CER carbon prices. Energy Policy 56, 434–445.

Pinho, C. and Madaleno, M., 2010. Hedging with $CO_2$ allowances: the ECX market. Working Papers in Economics, Departamento de Economia, Universidade de Aveiro.

Rittler, D., 2012. Price discovery and volatility spillovers in the European Union emissions trading scheme: a high-frequency analysis. Journal of Banking and Finance 36, 774-785.

Seifert, J., Uhrig-Homburg, M.,Wagner, M., 2008. Dynamic behavior of $CO_2$ spot prices. Journal of Environmental Economics and Management 56, 180-194.

Sousa, R., Aguiar-Conraria, L., 2014. Dynamics of $CO_2$ price drivers. University of Minho, NIPE Working Paper No. 2.

**See Ipag working papers on carbon emissions : http://ideas.repec.org/s/ipg/wpaper.html**

Ajmi A.N., El Montasser G., Nguyen D.K. (2014), "Carbon emissions – income relationships with structural breaks: the case of the Middle East and North African countries", Paper 2014-296, Ipag Business School.

Bunn D., Chevallier J., Le Pen Y., Sevi B., 2014. "Review of the Stochastic Properties of $CO_2$ Futures Prices", Working Papers 2014, Department of Research, Ipag Business School.

Chevallier J., 2014. "Review of the Stochastic Properties of $CO_2$ Futures Prices", Working Papers 2014, Department of Research, Ipag Business School.

Farhani S., Shahbaz M., Ozturk I. (2014), "Coal Consumption, Industrial Production and $CO_2$ Emissions in China and India", Working Papers 2014-225, Department of Research, Ipag Business School.

Farhani S., Shahbaz M., 2014. "What role of renewable and nonrenewable electricity consumption and output is needed to initially mitigate $CO_2$ emissions in MENA region?", Paper 2014-455,  Ipag Business School.

Farhani S., Shahbaz M., Arouri M., 2014. "Panel analysis of $CO_2$ emissions, GDP, energy consumption, trade openness and urbanization for MENA countries", Working Papers 2014-449, Ipag Business School.

Farhani S., Shahbaz M., Sbia R., Chaibi A. (2014), "What is MENA Region Initially Needed: Grow Output or Mitigate $CO_2$ Emissions?", Working Papers 2014, Department of Research, Ipag Business School.

Hammoudeh S., Nguyen D.K., Sousa R., 2014. "Energy prices and $CO_2$ emissions allowance prices: A quantile regression approach", Working Papers 2014-185, Department of Research, Ipag Business School.

Hammoudeh S., Nguyen D.K., Sousa R., 2014. "What explain the short-term dynamics of th prices of $CO_2$ emissions?", Working Papers 2014-081, Department of Research, Ipag Business School.

Hammoudeh S., Lahiani A., Nguyen D.K., Sousa R., 2014. "Asymmetric and nonlinear passthrough of energy prices to $CO_2$ emission allowance prices", Working Papers 2014-082, Ipag Business School.

Omri A., Nguyen D.-K. (2014), "On the determinants of renewable energy consumption: International evidence", Working Papers 2014, Department of Research, Ipag Business School.

Omri A., Nguyen D.-K. Rault C. (2014), "Causal interactions between $CO_2$ emissions, FDI, and economic growth: Evidence from dynamic simultaneous-equation models", Working Paper, Ipag Business School.

Shahbaz M., Ozturk I., Afza T., Ali A. (2014), "Revisiting the Environmental Kuznets Curve in a Global Economy", Working Papers 2014, Department of Research, Ipag Business School.

Zhu B., Ma S., Chevallier J., Wei Y. (2014), "Examining the structural changes of European carbon futures price 2005-2012", Working Papers 2014, Department of Research, Ipag Business School.

Zhu B., Wang P., Chevallier J., Wei Y. (2014), "Carbon price analysis using empirical mode decomposition", Working Papers 2014-156, Department of Research, Ipag Business School.

Zhu B., Ma S., Chevallier J., Wei Y. (2014), "Modelling the dynamics of European carbon futures price: a Zift analysis", Working Papers 2014-155, Department of Research, Ipag Business School.