Financial Turmoil in Carbon Markets

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***Abstract*—This paper assesses the impact of financial turmoil on carbon markets. For the assessment, we offer the price correlation model between financial and carbon assets using the supply and demand relationship. In particular, alternative investment behavior between securities and carbon assets is incorporated into the model. The model indicates that the correlation increases when stock prices plunge, referred to as contagion. Moreover, we show that the sudden redundancy of emission reduction, e.g., overallocation of EUAs in the EU-ETS, reduces the correlation between carbon and security prices by employing a jump diffusion model. Empirical studies using EUA futures prices, FTSE 100, and DAX show that the correlations between EUA and FTSE or DAX calculated from the Engle's DCC model tend to decrease in FTSE 100 or DAX, respectively. It results in the existence of contagion driven by financial markets. We also show that inverse leverage effects often observed in energy markets do not exist in all of EUA, FTSE 100, and DAX markets according to the price-volatility relationship. In addition, we show that the positive relationship between EUA futures prices and FTSE 100 or DAX indices for the phase II of the EU-ETS is more enhanced than the phase I of the EU-ETS.**

Keywords- EUA; FTSE; DAX; futures; dynamic conditional correlation; contagion; leverage effect

I. Introduction

Now the world is in the middle of the financial turmoil. Carbon markets are not the exception that is not influenced by this crisis. Since carbon markets are considered as an important tool to mitigate the carbon pollution economically, it will be meaningful to examine the relationship between financial crisis and carbon markets. Hence this paper highlights the impact of financial market crisis on carbon markets.

A number of studies have recently been conducted in carbon markets. Reference [1] proposes an equilibrium price model for EUA prices taking into account fuel switching between natural gas and coal fired power plants. Reference [2] employs AR-GARCH Markov switching price return model to capture the regime shifts between different phases of EU-ETS and the heteroskedasticty. Reference [3] compares existing popular diffusion and jump diffusion models, resulting in the favor of the geometric Brownian motion with jumps to fit historical EUA spot price data. Moreover, [4] proposes a stochastic price model where CO_2 prices do not have any seasonal pattern often observed in commodity markets. Reference [5] also proposes the mixed normal and mixed stable GARCH models to capture the heavy tail and volatility clustering in the U.S. SO_2 permits and EUA price returns. Reference [6] also shows that unique characteristics of convenience yield using EUA spot and futures prices, which differ between the phases I and II of the EU-ETS. While these studies shed lights on the modeling of carbon prices, they do not care about the relationship between carbon and financial markets. Reference [7] examined the impact of the EU-ETS on stock markets, in particular electric power corporations' stock prices. However, it did not examine the opposite influence such that the comprehensive performance of stock markets may affect the performance of carbon markets because it is considered that the financials play an important role in carbon markets. Figure 1 depicts the time series of EUA futures prices delivered on December, 2009 and FTSE 100. The figure seems to show that the carbon prices decrease when the stock index plunges. In this line, this paper assesses the impact of financial turmoil on carbon markets.

Fig. 1. EUA Futures Prices and FTSE 100

This paper proposes the price correlation model between stocks and carbon assets using the supply and demand relationship. In particular, alternative investment behavior between securities and carbon assets is incorporated into the model. The model indicates that the correlation increases when stock prices plunge referred to as contagion. Moreover, we show that the sudden redundancy of emission reduction, e.g., overallocation of EUAs in the EU-ETS, reduces the correlation between carbon and security prices by employing a jump diffusion model. Empirical studies using EUA futures prices, FTSE 100, and DAX show that the correlations between EUA and FTSE or DAX calculated from the Engle's DCC model tend to decrease in FTSE 100 or DAX, resulting in the existence of contagion driven by financial markets. We also show that inverse leverage effects often observed in energy markets do not exist in EUA, FTSE 100, and DAX markets according to the price-volatility relationship. In addition, we show that the positive relationship between EUA futures prices and FTSE 100 or DAX indices for the phase II of the EU-ETS is more enhanced than the phase I of the EU-ETS.

II. The Model

A. The Price Correlation Model for Stocks and Carbon Assets

Suppose that market participants with obligation in the EU-ETS possess the upward sloping marginal abatement cost curve. Then, the emission reduction is conducted by the difference between emission and allocation in the order of cheaper abatement measures. In our model, the oversupply of EUAs occurred in year 2006 is expressed by small emission reduction in the EU-ETS. The intersection between marginal abatement cost curve and the emission reduction volume determines the equilibrium price. To this end, the carbon price C is expressed using the marginal abatement cost (MAC) curve $g(\cdot)$ and emission reduction volume V:

$$C = g(V) = \left(1 + \frac{a_1 V}{c_1}\right)^{\frac{1}{a_1}}. \quad (1)$$

a_1 represents the curvature of the MAC curve and c_1 is the scale parameter. If $a_1 = 0$, (1) collapses to an exponential function.

Here we define the volume parameter V_C by $V_C = \bar{V}_C - V$ where $\bar{V}_C$ is a constant. From (1), carbon price C decreases in V_C. When carbon prices are low, it is expected that the volatility is high from the price similarity to securities as examined in [8]. Since the volatility has positive relationship to the volume parameter V_C, V_C can be considered as trading volume as the first order approximation.[1]

We try to model the carbon asset volume parameter (V_C) using the influence of security markets on carbon markets. Carbon markets may attract or distract financial players to obtain the trading profits when financial trading is active or not, respectively. Thus it is assumed that V_C is positively affected by stock trading volume (V_S). To support the assumption, we calculated 1-month rolling correlation between daily carbon and stock trading volume (ΔV_C and ΔV_S, resp.) using trading volume of EUA futures and FTSE 100 from January, 2008 to November, 2009. The result is illustrated in Figure 2. It suggests that positive correlations be dominated. V_C may be positively affected by V_S in the first order approximation.

Here the sensitivity of V_S on V_C is modeled using the parameter α which is positive and set to change with stock prices because price level may affect the investors' trading behavior. It is considered that investors will trade EUAs more to reduce the influence of stock market collapse on alternative investments of carbon assets when stock prices plunge. Hence, we set $\frac{\partial \alpha}{\partial S} < 0$. The volume models are represented by

$$dV_C = \alpha(S) dV_S + \sigma_{CV} du_t, \quad (2)$$
$$dV_S = \mu_{SV} dt + \sigma_{SV} dw_t, \quad (3)$$

[1]The reason for the approximation is that it allows for negative value.

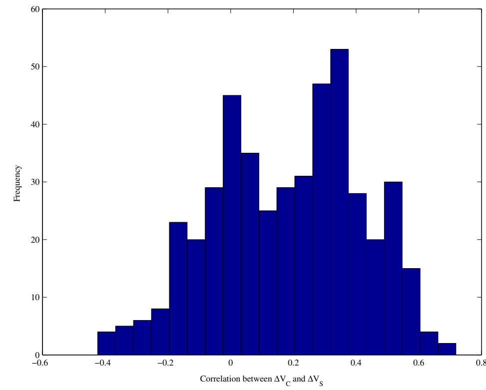

Fig. 2. Histogram of Correlation between ΔV_C and ΔV_S

where we assume that $E[du_t dw_t] = 0$ implying that du_t represents the orthogonal carbon trading volume fluctuation to equity trading volume fluctuation and that σ_{CV}, μ_{SV}, and σ_{SV} are constant.

Finally, an attempt to model security prices based on the trading volume is made as the first order approximation because we want to fully use the relationship such that carbon asset trading volume is affected by security trading volume as shown in Figure 2. Here we focus on supply and demand for security markets. There exist empirical evidences in security markets such that demand curve for shares demonstrates downward sloping as in [9]. On the other hand, [10] reports inelastic supply curve by examining a sample of 31 share repurchases. Then, as the empirical work to capture both supply and demand curves for stocks, [11] find that the demand curve is more elastic than the supply curve. Referring to the model of [12], the equilibrium prices are determined by the downward sloping demand curve and the stochastically fluctuated sum of supply and excess demand. Based on these empirical works, equilibrium prices may be determined by using the downward sloping demand curve and the stochastically fluctuated supply curve. Here we define by V_S supply related volume parameter. Hence, we built up equilibrium price model using the relationship between the downward sloping demand curve and the stochastically fluctuated volume parameter (V_S):

$$S = \left(1 + \frac{a_2(\bar{V}_S - V_S)}{c_2}\right)^{\frac{1}{a_2}}, \quad (4)$$

where $\bar{V}_S$ is a constant value. Equation (4) represents a decreasing demand function for the volume parameter assuming an inelastic supply curve for the volume. Stock prices decrease in V_S from (4). It is well-known that low S_t leads to high price volatility due to leverage effect, resulting in the positive relationship between the volatility and V_S. Hence, V_S can be considered the trading volume as the first order approximation.[2] Here a_2 represents the curvature of the demand curve and c_2 is the scale parameter, which is similar to the carbon asset model. If a_2 is null, then the model collapses

[2]Since V_S in this model allows for negative value, V_S is referred to as the approximation to the trading volume.

to a well-known exponential function. The increase of V_S produces stock price drop and carbon trading volume up from (4) and (2), respectively. Stock price plunge reflects the deteriorated company performance, resulting in low total emissions. It is consistent with the assumption of negative relationship between emission reduction volume and carbon trading volume.

Employing Ito's Lemma to these equations, the correlation model between stock and carbon price returns is calculated as

$$\frac{dC_t}{C_t} = \mu_C dt + \sigma_C d\nu_t, \tag{5}$$

$$\sigma_C = \frac{C_t^{-a_1}}{c_1}\bar{\sigma}_C, \tag{6}$$

$$\mu_C = \frac{C_t^{-a_1}}{c_1}(-\alpha\mu_{SV} + \frac{1-a_1}{2c_1}C_t^{-a_1}\bar{\sigma}_C^2), \tag{7}$$

$$d\nu_t = -\frac{1}{\bar{\sigma}_C}(\alpha\sigma_{SV}dw_t + \sigma_{CV}du_t), \tag{8}$$

$$\bar{\sigma}_C = \sqrt{\alpha^2\sigma_{SV}^2 + \sigma_{CV}^2}, \tag{9}$$

$$\frac{dS_t}{S_t} = \mu_S dt - \sigma_S dw_t, \tag{10}$$

$$\sigma_S = \frac{\sigma_{SV}}{c_2}S_t^{-a_2}, \tag{11}$$

$$\mu_S = \frac{S_t^{-a_2}}{c_2}\big(-\mu_{SV} + \frac{1-a_2}{2c_2}\sigma_{SV}^2 S_t^{-a_2}\big), \tag{12}$$

$$\begin{aligned}\rho_{CS} \equiv & \frac{1}{dt}\mathrm{Corr}\left(\frac{dC_t}{C_t}, \frac{dS_t}{S_t}\right) \\ = & \frac{\alpha(S)\sigma_{SV}}{\sqrt{(\alpha(S)\sigma_{SV})^2 + \sigma_{CV}^2}},\end{aligned} \tag{13}$$

If $a_1 = 0$ in (5), carbon prices follow a well-known lognormal process. If $a_1 > 0$, carbon prices demonstrate leverage effect from (6) because the volatility decreases in prices. The same properties hold for security prices. If $a_2 > 0$, security prices demonstrate leverage effect from (11), which describes negative correlation between security price returns and the volatility as in [16].

When we look at the correlation in (13), it demonstrates time varying due to the parameter $\alpha(S)$. Our interest nests in how the plunge of stock prices affects the correlation between stock and carbon price returns. To examine the relationship, we calculate the derivative of ρ_{CS} with respect to S:

$$\frac{\partial\rho_{CS}}{\partial S} = \frac{\partial\alpha}{\partial S}\frac{\sigma_{SV}\sigma_{CV}^2}{((\alpha(S)\sigma_{SV})^2 + \sigma_{CV}^2)^{\frac{3}{2}}}. \tag{14}$$

Since $\frac{\partial\alpha}{\partial S} < 0$ by definition, (14) is always negative: $\frac{\partial\rho_{CS}}{\partial S} < 0$. The model indicates that the correlation between carbon and stock prices increases when stock prices plunge. It may be considered as contagion driven by stock prices.

B. The Price Correlation Model with A Volumetric Jump

This subsection extends the correlation model to a sudden EUA over- and short-allocation case using a jump diffusion model and examines how it affects the correlation. For the EUA over- and short-allocation, the emission reduction volume V is suddenly decreased and increased, i.e., the trading volume V_C is suddenly increased and decreased, respectively. We represent V_C using a jump diffusion model:

$$dV_C = \alpha(S)dV_S + \sigma_{CV}du_t + jdN_t, \tag{15}$$

$$dV_S = \mu_{SV}dt + \sigma_{SV}dw_t. \tag{16}$$

N_t is a Poisson process with arrival intensity λ. jdN_t represents a sudden emission reduction redundancy, i.e., a sudden trading volume increase, due to irregular events such as the EUA overallocation in year 2006. Using Ito's Lemma and considering that carbon prices are obtained from the increasing MAC curve function of carbon trading volume, the correlation model between carbon and equity price returns is given by

$$\frac{dC_t}{C_{t-}} = \mu_C dt + \sigma_C d\nu_t + \frac{\Delta C_t}{C_{t-}}dN_t, \tag{17}$$

$$\frac{dS_t}{S_t} = \mu_S dt - \sigma_S dw_t, \tag{18}$$

$$\sigma_C = \frac{C_{t-}^{-a_1}}{c_1}\bar{\sigma}_C, \tag{19}$$

$$\mu_C = \frac{C_{t-}^{-a_1}}{c_1}(-\alpha\mu_{SV} + \frac{1-a_1}{2c_1}C_{t-}^{-a_1}\bar{\sigma}_C^2), \tag{20}$$

$$d\nu_t = -\frac{1}{\bar{\sigma}_C}(\alpha\sigma_{SV}dw_t + \sigma_{CV}du_t), \tag{21}$$

$$\sigma_S = \frac{\sigma_{SV}}{c_2}S_t^{-a_2}, \tag{22}$$

$$\mu_S = \frac{S_t^{-a_2}}{c_2}\big(-\mu_{SV} + \frac{1-a_2}{2c_2}\sigma_{SV}^2 S_t^{-a_2}\big), \tag{23}$$

$$\begin{aligned}\rho_{PS} \equiv & \frac{1}{dt}\mathrm{Corr}\left(\frac{dC_t}{C_{t-}}, \frac{dS_t}{S_t}\right) \\ = & \frac{\alpha(S)\sigma_{SV}}{\sqrt{\alpha^2\sigma_{SV}^2 + \sigma_{CV}^2 + (\frac{\Delta C_t}{g'(\bar{V}_C - V_{Ct-})})^2\lambda}},\end{aligned} \tag{24}$$

$$\Delta C_t = g(\bar{V}_C - (V_{Ct-} + j)) - g(\bar{V}_C - V_{Ct-}). \tag{25}$$

We take a look at the correlation in (24). The correlation is represented by the function of the sudden redundancy of emission reduction ΔC_t in (25), which lies in the denominator of the correlation. It implies that large jump size j reduces the correlation between carbon and equity price returns. In addition, the intensity λ is also in the denominator, implying that the frequency of jump reduces the correlation. If the sudden redundancy of emission reduction occurs like the overallocation of EUA observed in year 2006, the correlation between the price returns of carbon and equity will decrease.

III. Empirical Studies for EUA Futures Prices and Stock Indices

A. Data

We use the EUA futures prices delivered in December 2009, FTSE 100 index, and DAX index. FTSE 100 and DAX can be considered as the proxy of the European financial market movement. The data ranges from April 22, 2005 to November 27, 2009. They are the daily adjusted closing data. These data are obtained from the website of the European Climate

TABLE I
BASIC STATISTICS OF EUA, FTSE, AND DAX

	EUA	FTSE 100	DAX
Mean	19.78	5521.83	5949.60
Maximum	32.90	6732.40	8105.69
Minimum	8.20	3512.10	3666.41
Std. Dev.	4.64	776.88	1110.69
Skewness	0.02	-0.60	0.22
Kurtosis	2.41	2.39	2.06

Exchange and Yahoo finance. We illustrate the basic statistics of the data in Table I.

B. Correlation Structure between EUA and Stock Indices

In order to examine the relationship between EUA futures prices and FTSE 100 or DAX, we use the dynamic conditional correlation (DCC) model of [14]. We model the log return of the prices y_t using the Engle's DCC model as follows:

$$y_t = \epsilon_t \sim N(0, H_t), \tag{26}$$

$$\epsilon_t = D_t \eta_t, \tag{27}$$

$$D_t = \mathrm{diag}[h_{1,t}^{\frac{1}{2}} h_{2,t}^{\frac{1}{2}}], \tag{28}$$

where $y_t = (y_{1,t}, y_{2,t})'$, $\epsilon_t = (\epsilon_{1,t}, \epsilon_{2,t})'$, and $\eta_t = (\eta_{1,t}, \eta_{2,t})'$.[3]

For $i = 1,\ 2$, we have

$$h_{i,t} = \omega_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i h_{i,t-1}, \tag{29}$$

$$H_t = E[\epsilon_t \epsilon_t' \mid F_{t-1}] = D_t R_t D_t, \tag{30}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}, \tag{31}$$

$$Q_t = (1 - \theta_1 - \theta_2) Q + \theta_1 \eta_{t-1} \eta_{t-1}' + \theta_2 Q_{t-1}, \tag{32}$$

where Q_t^* is the diagonal component of the square root of the diagonal elements of Q_t.[4] Equation (29) represents a GARCH(1,1) effect for each price return, which may generally be observed in spot and futures markets. The conditional correlation is calculated using (31) where time varying conditional covariance is updated by (32). The scale parameters θ_1 and θ_2 represent the effects of previous standardized shock and conditional correlation persistence, respectively.[5] If either of the estimations of θ_1 or θ_2 as in (32) is statistically significant, the correlation structure of the pairs demonstrates time varying.

The estimation is conducted using two steps: First, conditional volatilities are estimated using univariate GARCH(1,1) model. Second, the parameters of the conditional variance are estimated using the standardized residuals obtained from the first step. Here the loglikelihood function (L) for the bivariate model is given by

$$L = -\frac{1}{2} \sum_{t=1}^{T} (2 \log 2\pi + 2 \log |D_t| + \log |R_t| + \eta_t' R_t^{-1} \eta_t). \tag{33}$$

After the estimation of parameters using the QMLE, the time-varying conditional correlations are empirically calculated using the errors (η_t) obtained from each GARCH(1,1) model.

In an attempt to calculate the correlation between EUA futures prices and FTSE 100, we estimate the parameters of the DCC model and obtain the dynamic conditional correlations. We illustrate the estimation (EST) results in Table II. Judging from the standard errors (SE), the parameters of α_i and β_i for both return series are statistically significant, resulting in the existence of the GARCH(1,1) effects for EUA futures prices and FTSE 100 indices returns, respectively. It suggests that both returns demonstrate heteroskedasticity, respectively. Then β_1 is smaller than β_2, implying that the volatility structure of EUA prices mean reverts more quickly than FTSE 100 indices. In addition, since the parameter estimate of θ_2 is also statistically significant, they have time varying correlation between EUA futures price and FTSE 100 returns. Moreover, Table II suggests that the correlation structure should comparatively keep long because θ_2 (0.972) is nearly close to unity. We also illustrate the estimation results for EUA futures prices and DAX in Table III. The same results to FTSE 100 are obtained for DAX.

Figure 3 illustrate the time-varying correlation between EUA and FTSE 100 calculated by using the transformed standardized residuals of the univariate GARCH(1,1) model estimations. The result captures almost the positive linkage between EUA futures price and FTSE 100 returns. While negative correlations are observed between the middle of year 2006 and the inception of year 2007, the period experienced the overallocation of EUAs, resulting in the plunge of EUA

TABLE II
PARAMETER ESTIMATES OF DCC MODEL FOR EUA FUTURES PRICES AND FTSE 100

	ω_1	α_1	β_1	ω_2	α_2	β_2	θ_1	θ_2
EST	5.240E-5	0.213	0.745	1.070E-6	0.117	0.883	0.019	0.972
SE	1.478E-5	0.076	0.048	5.228E-7	0.018	0.017	0.012	0.021
L	6.207E+3							
AIC	-1.240E+4							
SIC	-1.236E+4							

TABLE III
PARAMETER ESTIMATES OF DCC MODEL FOR EUA FUTURES PRICES AND DAX

	ω_1	α_1	β_1	ω_2	α_2	β_2	θ_1	θ_2
EST	5.240E-5	0.213	0.745	2.480E-6	0.103	0.889	0.021	0.971
SE	1.478E-5	0.076	0.048	1.121E-6	0.022	0.020	0.010	0.016
L	6.039E+3							
AIC	-1.206E+4							
SIC	-1.202E+4							

[3] The constant terms in (26) were not statistically significant for EUA futures, FTSE 100, and DAX log returns.

[4] Define $Q_t \equiv \begin{pmatrix} q_{11} & q_{12} \\ q_{21} & q_{22} \end{pmatrix}$. Then, $Q_t^* = \begin{pmatrix} \sqrt{q_{11}} & 0 \\ 0 & \sqrt{q_{22}} \end{pmatrix}$.

[5] θ_2 represents the persistence of the conditional covariance matrix. Since the standardized shock η_t is used for the calculation, θ_2 is approximately considered as the conditional correlation persistence.

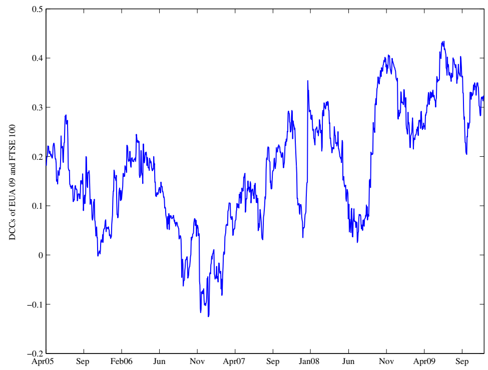

Fig. 3. Dynamic Conditional Correlations of EUA Futures Prices and FTSE 100

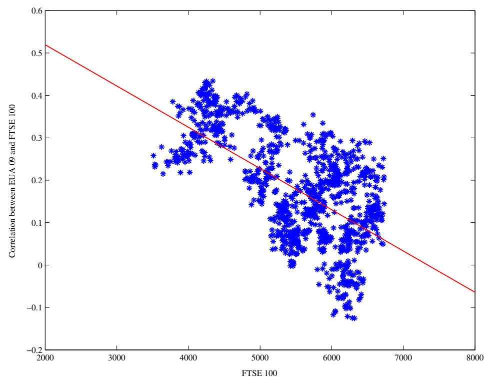

Fig. 4. Scatter Plots between DCC and FTSE 100

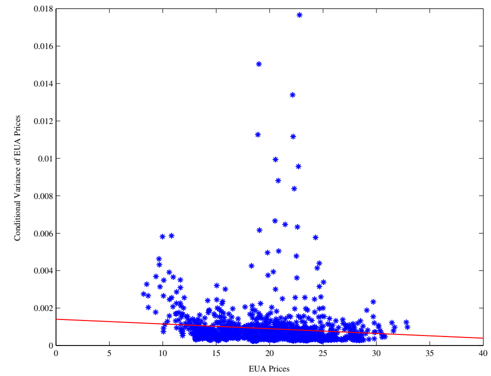

Fig. 5. Conditional Variance of EUA Price Returns and EUA Prices

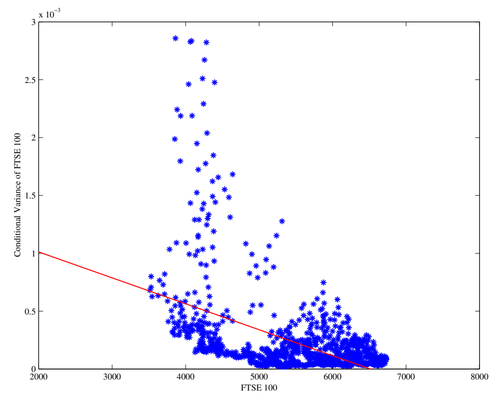

Fig. 6. Conditional Variance of FTSE Returns and FTSE

prices. The same results were obtained for DAX. The correlation structure between EUA futures and financial indices holds independently with FTSE and DAX price movement, inducing the negative correlations. In addition, judging from (13), almost the positive correlations give rise to positive $\alpha(S)$, implying that carbon asset trading volume increases in FTSE and DAX trading volume.

In order to examine the relationship between EUA prices and the correlations, we illustrate the scatter plots between the conditional correlations and FTSE 100 in Figure 4. The correlations tend to decrease in FTSE 100. Adjusted R^2 is calculated as 38.3% in this case. It suggests that the characteristics are different from commodities as in [15] that treats the correlation between energy and agriculture. It also suggests that the contagion can be seen in carbon markets because of high correlation between EUA futures prices and FTSE 100 during low index price periods. On the other hand, we could not find significant impact of EUA prices on the correlations in contrast to Figure 4. Hence, the correlation reduction is not driven by EUA prices but by FTSE 100, resulting in the financial market-driven contagion to EUA futures markets. Almost the same results are obtained for DAX.

Then we examine the relationship between volatility and price of EUA and FTSE, respectively. For that purpose, we calculated the conditional variance of EUA price and FTSE returns using (30). The results are reported in Figures 5 and 6. For EUA, we found that the conditional variance is negatively but very weakly related to the price. Here the regressed line in Figure 5 has 0.9 % adjusted R^2. Then, for FTSE, the conditional variance decreases in the prices. The regressed line demonstrates 23.0 % adjusted R^2. Hence we found that leverage effect exists weakly in the EUA market and strongly in the FTSE market. Taking into account that one of well-known characteristics for energy commodities is the inverse leverage effect, we may conclude that both the EUA and FTSE markets are quite different from energy commodity markets with respect to the price-volatility relationship. The same results are obtained for DAX indices.

C. Comparison between Phase I and Phase II of EU-ETS

To examine the differences of the EUA-FTSE DCCs for the phase I and phase II of EU-ETS, we conduct the same calculations to the previous subsection using two subsets of the data: from April 22, 2005 to December 31, 2007 and from January 2, 2008 to November 27, 2009. The results are illustrated in Figures 7 and 8, respectively. Figure 7 indicates that the correlations between EUA and FTSE are relatively low while they are time varying. On the other hand, Figure 8 demonstrates that the correlations between EUA and FTSE DCCs are relatively high. Hence the phase II seems to enhance the relationship between EUA and FTSE more than phase I. This may be due to the large amount of trading transacted

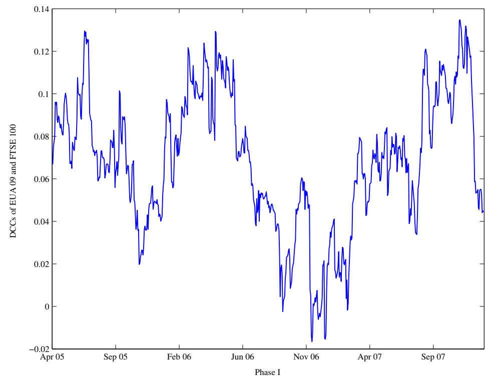

Fig. 7. DCCs of EUA Futures Prices and FTSE 100 (Phase I)

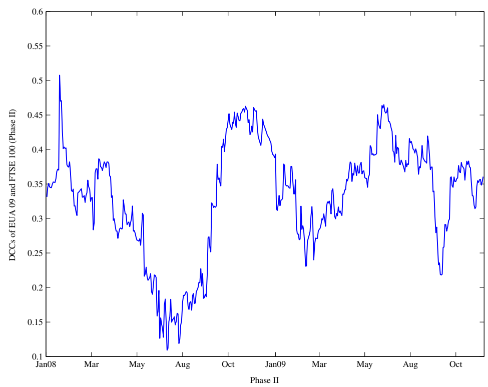

Fig. 8. DCCs of EUA Futures Prices and FTSE 100 (Phase II)

by financial players in the phase II more than the phase I reflecting the development of the EU-ETS. The same outcomes are obtained for DAX.

IV. Conclusions

This paper has assessed the impact of financial turmoil on carbon markets. We have offered the price correlation model between stocks and carbon assets using the supply and demand relationship. In particular, alternative investment behavior between securities and carbon assets was incorporated into the model. The model indicated that the correlation increases when stock prices plunge referred to as contagion. Moreover, we have shown that the sudden redundancy of emission reduction, e.g., overallocation of EUAs in the EU-ETS, reduces the correlation between carbon and security prices by employing a jump diffusion model. Empirical studies using EUA futures prices, FTSE 100, and DAX have shown that the correlations between EUA and FTSE or DAX calculated from the Engle's DCC model tend to decrease in FTSE 100 or DAX, respectively. It results in the existence of contagion driven by financial markets. We also have shown that inverse leverage effects often observed in energy markets do not exist in EUA, FTSE 100, and DAX markets according to the price-volatility relationship. In addition, we have shown that the positive relationship between EUA futures prices and FTSE 100 or DAX indices for the phase II of the EU-ETS is more enhanced than the phase I of the EU-ETS. This may be due to the large amount of trading transacted by financial players in the phase II more than phase I reflecting the development of the EU-ETS.

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