Co-movements between carbon, energy and financial markets

A multivariate GARCH approach

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Abstract

This paper explores how price linkages between carbon allowances and market fundamentals in the EU Emissions Trading Scheme (EU ETS) vary over time. I adopt a multivariate GARCH model that allows the conditional correlation between carbon, energy and financial prices to change smoothly across regimes governed by functions of two transition variables that explain why price linkages vary. I use (i) time as transition variable to allow for structural changes associated with institutional advances in the EU ETS and (ii) implied volatility to account for heterogeneity in the behavior of correlations in times of distress compared to calm periods. The results point to a new pricing regime with much closer carbon-energy price linkages in the second phase of the EU ETS. Furthermore, I find that correlations depend on market uncertainty conditions, which exposes the link between carbon and financial markets due to common macroeconomic shocks during the current financial crisis.

Keywords: CO_2 emissions trading, EU ETS, energy markets, financial markets, multivariate GARCH.

1 Introduction

Putting a price on carbon dioxide (CO_2) emissions is a fundamental lesson from environmental economics and the theory of externalities. The introduction of the European Union Emissions Trading System (EU ETS) has established by now the world largest emissions allowance market (henceforth carbon market) in which the tradable EU Allowances (EUAs) reflect the EU-wide carbon price. Much recent effort has been made to explore the carbon pricing mechanism. Theory predicts that the allowance price should reflect market fundamentals related to the marginal costs of emissions abatement (Rubin, 1996). Energy prices (e.g. coal prices) and economic indicators (e.g. stock prices) are widely accepted fundamentals correlated

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with the observed EUA market prices (Hintermann, 2010). However, regulatory events and the financial crisis have substantially changed the EU ETS during its seven years (2005-2011) of operation. Although central to understanding price formation in the EU ETS, the consequences of these structural changes on price linkages remain widely unexplored.

In this paper I investigate *how* price linkages between EU allowances and market fundamentals vary *over time* both within and between trading phases of the EU ETS. I set up a data-coherent model of the correlation process between EUAs and a set of accepted fundamentals (oil, gas, coal, electricity, stocks and bonds), allowing for the correlations to vary across regimes directly as a function of transition variables, thereby explaining *why* price linkages vary. Two variables, a time trend and implied stock market volatility, combine to capture variations of correlations associated with (i) institutional changes in the maturing EU ETS and (ii) risk perception in financial markets. My approach is designed to accommodate, for the first time, the presence of structural breaks in price linkages triggered by policy events and the different behavior of price correlations in times of distress compared to calm periods.

Previous research has focused on ascertaining whether carbon prices are based on marginal abatement cost determinants. This approach is well represented by Hintermann (2010) who derives a structural model that explains EUA price changes as a function of, inter alia, energy prices, stock market indices and weather. However, the detection of fundamental price drivers is only one side of the story. My work is motivated by empirical studies in financial economics that suggest price formation across markets evolves over time (Bollerslev et al., 1988) and can be materially influenced by institutional changes (Capiello et al., 2006) or time-varying market uncertainty (Longin and Solnik, 1995, 2001). None of the existing studies on the EU ETS is based on an econometric model that accounts for such dynamics in price linkages. The way they incorporate institutional and macro-financial changes of the EU ETS environment (sample-splitting and/or dummy variables) is mostly ad-hoc (see also Bredin and Muckley, 2011; Alberola et al., 2008). Instead, my approach seeks to formulate a coherent model of the data-generating process that includes the possibility of structural change in the dependence structure between EUAs and its fundamentals. Extending econometric approaches used in the EU ETS literature, I apply a multivariate GARCH framework and model dynamic conditional correlations to trace temporal patterns in price linkages and their economic sources.

I attempt to examine two distinct, but related, empirical questions. The first question centers on structural breaks and asks whether a new correlation regime with an increased dependency between EUAs and fundamentals emerges in the EU ETS over time. I argue that advances in the market design and maturity of the relatively young EU ETS spur structural breaks in the Phase I-to-Phase II period with upward trends in carbon-energy correlations. First, various institutional rules of the EU ETS which proved inefficient in Phase I considerably changed, e.g. the ban on intertemporal trading of EUAs (Daskalakis et al., 2009). Second, market microstructure analyses indicate that the EU ETS has become a highly liquid market with the common trading patterns of mature commodity markets (Mizrach and Otsubo, 2011) which may entail enhanced informational efficiency (Chung and Hrazdil, 2010).

My second empirical question focuses on correlation asymmetries under different market uncertainty conditions and asks whether correlations are exacerbated during episodes of financial turmoil. I suggest that the risk perception in financial markets is important for understanding carbon-energy and carbon-financial market correlations and ultimately the EUA price formation. In fact, the 2008-09 financial crisis has been characterized by sharp price falls across various markets, thereby witnessing a growing connection between carbon, energy and financial market prices. The different correlation behavior in times of distress to calm periods should be particularly relevant to uncover carbon-financial market linkages. Prior findings suggest that EUA prices are only remotely connected to stock and bond markets (Chevallier, 2009). I re-examine this apparent segmentation since, in theory, common macroeconomic shocks should connect the markets.

I adopt the Double Smooth Transition Conditional Correlation GARCH model by Silvennoinen and Teräsvirta (2005, 2009) that allows the conditional correlation to change smoothly across up to four regimes directly as a function of observable transition variables. I use smooth transition models because they can capture both gradual and sudden changes in correlation patterns, impounding slowly developing trends (i.e. due to institutional change) and rapid changes in investor expectations (i.e. due to shifts in risk perception). Another appealing feature of these models is that they provide a framework in which constancy of correlations and the existence of links to economic variables or general proxies for latent factors can be tested in a straightforward fashion. I use (i) calendar time as transition variable to capture shifts in the correlation level and (ii) the implied volatility from equity index options (VSTOXX index) to account for expected market uncertainty conditions.

My main findings are as follows: First, correlations between carbon, on the one hand, and gas, coal and electricity, on the other hand, are four, three and two times as high in Phase II as in Phase I, respectively. The structural breaks are characterized by widely varying dates and speeds of change illustrating the advantages of endogenously determining change points. The tendency towards greater market integration evolves to some extent gradually in the course of 2007 indicating an efficient anticipation of changes in the EU ETS. Second, carbon and financial markets are not segmented. Rather, correlations heavily depend on market conditions and the VSTOXX index is an informative state variable concerning the risk of common shocks often associated with extreme events. High expected market volatility shifts carbon-stock (-bond) correlation significantly upwards (downwards) with peaks around the Lehman Brothers failure. Third, the striking commonality between carbon-oil and carbon-stock linkages over time indicates that the - ambiguous - positive price impact of oil is attributed to the correlation between oil prices and overall economic activity rather than to fuel switching or oil-gas correlation.

Overall, my findings suggest that a new pricing regime with an increased dependency between EUA prices and energy prices has emerged in Phase II of the EU ETS. The stabilized price linkages indicate that energy market fundamentals become more important in the EUA price formation. This would have a positive effect on the cost-efficiency of the EU ETS, that is to achieve emissions reduction goals at minimum costs. My findings bear practical implications for risk management of companies and specialized traders; optimal hedging strategies have changed as a result of correlation shifts and efficient hedging positions for asset holdings should be based on time-varying correlation estimates. The implied volatility index may partly help on hedging the risk of adverse price movements in periods of turmoil.

2 EU Emissions Trading Scheme

The EU ETS covers almost 50% of EU's total CO_2 emissions produced by around 12,000 covered installations in the power sector and most energy-intensive industries. To date, three regulatory periods have been put in place: The pilot Phase I covered the period 2005-2007. Phase II coincides with the Kyoto Protocol commitment period of 2008-2012. Phase III will run from 2013-2020. An extensive stream of literature discusses the lessons learned from the first trading years (e.g., Convery et al., 2008). The decentralized cap-setting process, the grandfathering of allowances and the restriction of inter-phase banking of allowances are identified as flaws of the initial regulatory setting. The latter made Phase I a self-contained market unrelated to future caps and together the institutional weaknesses led to a general over-allocation and spot price collapse. In contrast, Phase II experiences considerable improvements (Egenhofer et al., 2011). First, over-allocation is avoided as the European Commission assesses national allocation plans and, thereby, de facto imposes a EU-wide cap. Also, the use of auctioning as allocation procedure increases. Second, banking of EUAs from Phase II into later phases is allowed. Finally, Kyoto Protocol emission credits are introduced.

Beside the distinct regulation, Phase I and II also differ in terms of market expertise and liquidity. To begin with, the difference is reflected in the total market volume of EUA trading; it was 2,410 million metric tons of CO_2-equivalent in Phase I, which is less than half of the volume traded (4,940 million metric tons) in the single year 2009 (according to Point Carbon). Further, market microstructure analyses of Benz and Hengelbrock (2008) and Bredin et al. (2011) document an increase in market liquidity for Phase II expiring futures contracts. Also, Mizrach and Otsubo (2011) suggest that market activity in Phase II resembles the trading patterns of other more mature instruments in a highly liquid market.

The structural change with respect to market regulation, expertise and liquidity motivates me to devise a statistical methodology that allows for the price linkages in the EU ETS to change over time. Previous studies (e.g. Mansanet-Bataller et al., 2007; Hintermann, 2010) make a major contribution to understanding carbon price formation, but none are based on a convincing model flexible enough to capture dynamic linkage patterns with likely structural breaks, time trends and correlation asymmetries.

3 Data

3.1 Data specification

I consider daily data for the sample period from April 22, 2005 until April 21, 2011, a total of 1,537 observations. The price data is obtained from ICE Futures Europe and Thomson Datastream and denominated in the local currency of each market.[1]

Carbon data: I use settlement prices of EUA futures contracts traded on the ICE ECX to construct a continuous price series that combines five contracts with expiration in Phase II (December 2008, 2009, 2010, 2011). During Phase I, the carbon price series is equal to the price of the December 2008 contract. In Phase II, the series switches to the December 2009 contract, until its last trading day, whereupon the series switches into the next yearly contract. Hence, over the entire sample period I rely on futures contracts which are not redeemable in Phase I. I make this choice for several reasons. First, transactions and volumes in the futures market are much higher than in spot markets (Kossay and Ambrosi, 2010). Second, the time series for EUA Phase I prices is contaminated by the banking ban, which made Phase I spot and futures contracts a different asset. Thus, real market activity shifted toward Phase II allowances and Phase II futures prices can be considered as the reliable price signal (Convery et al., 2008). Third, the ICE ECX market is the leading venue where 90% of the EUA price discovery takes place and the December expiries are the most active contracts (Mizrach and Otsubo, 2011).

Energy data: The oil price is the 1-month forward Brent futures contract. The price of gas is the 1-month ahead contract for natural gas negotiated at the National Balancing Point (NBP). I consider this gas price, since it is the most liquid gas trading point. The coal price used is the 1-month ahead API 2 futures contract delivered to Amsterdam, Rotterdam and Antwerp (ARA). For electricity prices I use ICE UK 1-month futures for baseload power.

Financial data: For equities I use the EURO STOXX 50 price index. The index covers 50 blue-chip stocks from 12 euro area countries. I choose this equity index because it serves as basis for the EURO STOXX 50 Volatility Index (see below).[2] For bonds, I use a Datastream-constructed 10-year benchmark government bond index for the European Monetary Union.[3]

Transition variables: The first is calendar time, scaled as t/T where t is the current observation number and T is the sample size. The second is the level of the EURO STOXX 50 Volatility Index (VSTOXX). The index is designed to reflect the market expectations of volatility by measuring the square root of the implied variance across all EURO STOXX 50 options over the next 30 days. It is, by construction, a

[1] Estimates using data denominated in a common currency, i.e. EUR, have also been performed with the results remaining qualitatively the same.

[2] For robustness, I also evaluate the broader STOXX EUROPE 600 index. Results remain qualitatively very similar but due to space limitations are not presented here. They are available upon request.

[3] I choose long-term bonds over short-term bonds because monetary policy is more likely to have a confounding influence on the latter (e.g. Christiansen, 2000). Examining corporate bonds is left for future research.

forward-looking (implied) volatility measure rather than a description of present volatility (see Connolly et al., 2007).

3.2 Summary Statistics

Results of the ADF and KPSS tests in Table 1 (Panel B) suggest taking first differences to obtain stationary time series at conventional significance levels in all cases. As (logarithmic) price series are non-stationary, I also test for pairwise cointegration among EUA and energy/financial prices based on the Johansen procedure, but find no evidence thereof.[4] Consequently, prices are transformed into continuously compounded returns by taking natural logarithms, differencing, and multiplying by 100. Panel A of Table 1 contains descriptive statistics for the return series which all exhibit the standard properties of high-frequency asset returns; they are skewed, fat-tailed and a Gaussian distribution is unambiguously rejected. Panel C summarizes information about the presence of autocorrelation and ARCH effects. Where relevant, I will include autoregressive terms in the mean equation to account for serial correlation. The strong signs of volatility clustering for all series point towards an ARCH parametrization for second moments and motivate the use of a multivariate GARCH-type framework to model co-movements between the correlated heteroskedastic time series.

[Table 1 about here]

4 Econometric Methodology

4.1 Multivariate GARCH framework

Consider a stochastic $N \times 1$ vector of logarithmic asset returns $y_t = \{y_{i,t}\}$ at time t is described by the following model

$$y_t = E\left(y_t \mid \Omega_{t-1}\right) + \varepsilon_t \tag{1}$$
$$\varepsilon_t = H_t^{1/2} z_t \tag{2}$$

where Ω_{t-1} is the information set about the series up until $t-1$, and ε_t is a $N \times 1$ vector of residuals. Each conditional mean in y_t is modeled as univariate autoregressive process with orders P (AR(P)). The error process ε_t is specified by its $N \times N$ full rank conditional covariance matrix H_t which is assumed to follow a time-varying structure, and z_t, a $N \times 1$ random error vector that is assumed to be i.i.d. with $E\left(z_t\right) = 0$ and $Var\left(z_t\right) = I_N$.

The covariance matrix H_t can be decomposed into a diagonal matrix of conditional standard deviations D_t and a matrix of conditional correlations P_t

[4] The results are contained in an appendix that is available upon request.

$$H_t = D_t P_t D_t \tag{3}$$

$$D_t = diag\left(h_{11,t}^{1/2} \dots h_{NN,t}^{1/2}\right) \tag{4}$$

$$P_t = (\rho_{ij,t}) \text{ with } \rho_{ii,t} = 1 \tag{5}$$

To ensure the positive definiteness of H_t, it is sufficient to constrain the correlation matrix P_t to be positive definite at each point in time. The conditional variances $h_{ii,t}$ in (4) are assumed to follow a univariate GARCH(P,Q) process defined as

$$h_{ii,t} = \omega + \sum_{p=1}^{P} \alpha_p \varepsilon_{ii,t-p}^2 + \sum_{q=1}^{Q} \beta_q h_{ii,t-q} \tag{6}$$

To keep the analysis traceable, the natural starting point is a GARCH(1,1) specification, where the future variance will be an average of the current shock, ε_{t-1}^2, and the current variance, h_{t-1}, plus a constant. To ensure the conditional variances are uniformly positive, the coefficients of a GARCH model must be restricted; in a GARCH(1,1), $\omega > 0$, $\alpha \geq 0$ and $\beta \geq 0$.

In order to complete the definition of the model I have to specify the conditional correlation matrix in (5).

4.1.1 Constant Conditional Correlation

The simplest multivariate correlation model that is nested in other models, is the Constant Conditional Correlation (CCC) GARCH model of Bollerslev (1990).[5] This model restricts the conditional correlations matrix between the separate univariate GARCH processes to be time-invariant. More specifically, $H_t = D_t P D_t$ with $P = (\rho_{ij})$. Although the CCC GARCH model simplifies the estimation of parameters, the assumption that conditional correlations are constant is unrealistic in many empirical applications. Therefore, the model provides a benchmark for setting the augmented models below and for testing the constancy of correlations.

4.1.2 Smooth Transition Conditional Correlation

In the Smooth Transition Conditional Correlation (STCC) GARCH model of Silvennoinen and Teräsvirta (2005), the conditional correlation matrix P_t is a convex combination of two positive definite matrices $P_{(1)}$ and $P_{(2)}$ each corresponding to an extreme state of constant correlation. The correlation structure varies smoothly between the two extreme states of constant correlations as a function of a transition variable. More specifically, the following dynamic structure is imposed on the conditional correlation

$$P_t = (1 - G_t) P_{(1)} + G_t P_{(2)} \tag{7}$$

[5] For recent surveys of multivariate GARCH models see Bauwens et al. (2006).

where $P_{(1)} \neq P_{(2)}$, and $G(\cdot) : \mathbb{R} \to (0,1)$ is a monotonic function of an observable transition variable $s_t \in \Omega_{t-1}$. The transition function is the logistic function

$$G_t = \left(1 + e^{-\gamma(s_t - c)}\right)^{-1}, \ \gamma > 0 \tag{8}$$

where c is the threshold parameter that determines the location of the transition, and γ determines the slope of the function, that is, the speed of transition. When the transition variable s_t has values less than c, the correlations are closer to the state defined by $P_{(1)}$ than the one defined by $P_{(2)}$, and vice versa. As motivated above, the transition variables here are (i) calendar time or (ii) the VSTOXX index. When γ converges to infinity, the transition function becomes a step function and the transition between the two extreme correlation states becomes abrupt. Then, the STCC model approaches a structural break model in conditional correlations. Bollerslev's CCC model is obtained from the STCC model by setting either $P_{(1)} = P_{(2)}$ or $\gamma = 0$.

Having estimated a STCC GARCH model to the data at hand, the researcher may wonder whether the transition variable of the fitted model is the sole factor influencing conditional correlations over time. That is, whether there exists an additional factor that might affect correlations and that should not be ignored. This brings me to another model extension.

4.1.3 Double Smooth Transition Conditional Correlation

In the Double Smooth Transition Conditional Correlation (DSTCC) GARCH model, Silvennoinen and Teräsvirta (2009) extend the original STCC GARCH model by allowing the conditional correlation to vary between four extreme correlation states smoothly governed by logistic functions of two transition variables.

$$P_t = (1 - G_{2t})\left((1 - G_{1t})\, P_{(11)} + G_{1t} P_{(21)}\right) + G_{2t}\left((1 - G_{1t})\, P_{(12)} + G_{1t} P_{(22)}\right) \tag{9}$$

$$G_{it} = \left(1 + e^{-\gamma_i(s_{it} - c_i)}\right)^{-1}, \ \gamma_i > 0, \ i = 1,2 \tag{10}$$

The DSTCC approach introduces extra flexibility by combining the VSTOXX index with calendar time. If $s_{2t} = t/T$, at the beginning of the sample when $t/T < c_2$, correlations move between $P_{(11)}$ and $P_{(21)}$ depending on the transition variable $s_{1t} = VSTOXX_{t-1}$: when $s_{1t} < c_1$, the correlations are closer to the state in $P_{(11)}$ than in $P_{(21)}$, and when $s_{1t} > c_1$ the situation is opposite. Accordingly, as time evolves and $t/T > c_2$, $P_{(12)}$ and $P_{(22)}$ are the corresponding states at the sample end and $s_{1t} = VSTOXX_{t-1}$ drives the correlation between these two matrices.

4.2 Estimation procedure

I estimate the bivariate structure of the presented models by a quasi-maximum likelihood (QML) procedure. I start with the estimation of the CCC GARCH model with a constant level of correlation for each bivariate combination. Then, I subsequently test the hypothesis that conditional correlations are constant. This is of paramount importance before estimating a (D)STCC GARCH model because some of the parameters of the alternative model are not identified if the true model has constant conditional correlation and thus, estimating the models without first testing the constancy hypothesis may lead to inconsistent parameter estimates. I employ a LM-type test procedure developed by Silvennoinen and Teräsvirta (2005, 2009). These tests are conditioned on a particular transition variable and essentially ascertain whether that particular variable affects conditional correlations.[6]

5 Results

5.1 Conditional mean and volatility

The results for the conditional mean y_{it} and conditional variance h_{it} estimation are very close to those reported in prior studies (Benz and Trück, 2008; Chevallier, 2009) and, for the sake of brevity, I do not present them. The AR lag length (P) is determined using the Bayesian Information Criteria (BIC) and produces serially uncorrelated residuals. A first-order GARCH model performs sufficiently well for all considered series. The resulting standardized residuals show no signs of remaining serial correlation or ARCH effects. I also check for asymmetries using the GJR GARCH model of Glosten et al. (1993). Yet, most series show no significant asymmetric term and/or I notice that the BIC does not decrease when replacing the standard GARCH specification.[7]

5.2 Conditional correlation

5.2.1 Choosing the transition variable

The evidence on changing correlations from the LM-type test procedure can be summarized as follows. First, calendar time is an indicator of change in correlations (first column of Table 2): the null hypothesis of constant correlations is rejected at the 1% significance level for every bivariate combination, except for the case of carbon-bond at 5% level. Second, the volatility index seems to be a weaker indicator of change than time (second column of Table 2). The LM test with the one-day lag of the VSTOXX index[8] as transition variable rejects only four out of the six cases. Yet, the rejection for the carbon-oil,

[6] A description of the QML estimation and LM-test procedure and results for the CCC GARCH model are contained in an appendix that is available upon request.

[7] The full set of mean and volatility estimation and specification test results is available upon request.

[8] In order to facilitate the comparison of models below, I use the one-day lag of the VSTOXX index, so that the (D)STCC GARCH estimations are based on the same information set as the CCC and DCC GARCH models.

-coal, -stock, -bond correlation dynamics is very strong and the VSTOXX index turns out to have the best performance for these pairs. As expected, the market uncertainty indicator conveys highly valuable information for the carbon and financial market linkages; for carbon-stocks I observe the strongest overall rejection. The high p-values for carbon-gas and carbon-electricity indicate that the correlation dynamics between these markets are not directly related to the perceived level of volatility in financial markets, which is in sharp contrast to the dynamics between carbon and oil as well as carbon and coal.

[Table 2 about here]

Table 2 also reports the LM_{STCC} test which evaluates whether an second transition that depends directly on time would provide a better description of correlation dynamics than a smooth transition model with (i) the VSTOXX index as the sole transition variable (third column) or (ii) a single time trend (last column). Evidence in favor of the double transition model with $s_{1t} = VSTOXX_{t-1}$ and $s_{2t} = t/T$ is found only in one case, namely for the carbon-coal link. Moreover, the tests indicate a non-monotonic relationship between calendar time and correlations for the carbon-financial, carbon-oil and carbon-gas link.

Finally, (i) the strength of rejection of the null in the LM_{CCC} is used as criterion for selecting the most relevant transition variable in a STCC GARCH model and (ii) the strength of rejection of the null in the LM_{STCC} is used as criterion to discriminate between a single and double smooth transition specification (all corresponding p-values are listed in bold type in Table 2). Based on these criteria, the best models are chosen for each bivariate system. Note that I select a STCC specification for carbon-gas due to the relatively weak support for a double transition dynamic.

Figures 1 and 2 plot the estimated time-varying conditional correlations implied by the selected smooth transition models whereas Table 3 reports all estimated parameters.

[Table 3 about here]

5.2.2 Carbon-energy market correlation

Beginning with the energy market group, conditional correlations between carbon and oil switch between a low (0.19) and high (0.37) correlation state when expected stock volatility (i.e. the VSTOXX index) is high, with a sustained increase during the 2008-09 period and in early 2010. The estimated transition is rather abrupt, and one may thus speak of low and high volatility regimes. The latter regime occurs when the VSTOXX index exceeds c=25.45, which is the case in about 36% of the observations. This corroborates prior evidence that oil and carbon prices are closely linked (Mansanet-Bataller et al., 2007; Alberola et al., 2008), whereby I further document that this link is directly related to the perceived level of volatility in financial markets and stronger in turbulent times. Indeed, the carbon-oil linkage is a special case in the energy market group; there is a striking temporal commonality in the correlation pattern between carbon-oil and carbon-stock markets (see below) and market uncertainty conditions are the common driving factor. This finding sheds new light on the underlying reason for the positive influence of oil prices on carbon prices. Prior studies discuss whether the oil price effect can be attributed to a fuel switching effect, to the correlation between the oil and gas price, or rather to the correlation between the oil price to economic activity (e.g. Rickels et al., 2010). The result that times with stronger carbon-oil correlation are also likely to be times with stronger carbon-stock correlations suggests that the link to the economic activity is the driving force behind the oil price impact.

[Figure 1 about here]

The carbon-coal correlations have four states, transitioning on VSTOXX and time. In the sample up to the first quarter of 2008 correlations are weak (0.09) and high expected stock market uncertainty even decreases correlations (to 0.07), yet this effect is statistically not significant. In contrast, later in the sample, correlations shift from 0.35 to 0.44 during high VSTOXX states. Again, the correlation profile shows a clear peak during the 2008-09 crisis. The estimated location parameter c for the VSTOXX index is above 26 and transitions are very rapid. It is important to note, however, that regardless of the state of uncertainty, I detect a time break with a remarkable increase in the overall level of carbon-coal correlations. The break date is April 2008, the month in which EU ETS participants have to surrender their allowances for the last trading year of Phase I. Indeed, with the start of Phase II, correlations are at least four times as high as in the first trading period ($P_{(11)}$vs. $P_{(12)}$).

Similar breaks in the correlation regime show up for carbon-gas. In this case the estimates point to a continuous and gradual rise (γ=29.8) of carbon-gas correlations, while for carbon-coal the change is rather abrupt. In sum, the overall level of correlation almost triples, from 0.09 to 0.26. The transition phase spans the period from January 2007 to February 2008, whereas the change is relatively rapid in August 2007 (c=0.39). Thus, the increase mostly occurs within the last trading year of Phase I. The range of correlations is in agreement with the DCC GARCH results of Koenig (2011), however, the correlations in his model fluctuate widely and as a result evolving trends and time breaks cannot be revealed.

Examining carbon-electricity linkages, I find another noticeable break in the correlation structure. Again, by the end of Phase I (October 2007) correlations instantaneously climb to levels almost twice as high (from 0.18 to 0.32). This may have crucial implications for power generation companies and their ability to hedge the risk of adverse price movements. Following Roques et al. (2008) the cash flows of a power plant are self-hedged to the extend that electricity, fuel and carbon prices positively co-move. In fact, my findings suggest that the self-hedging capacity of UK power plants, which are mostly gas-fired, is even stronger in Phase II of the EU ETS, because EUA and UK electricity prices as well as EUA and gas prices both exhibit strong and positive co-movements.

Summing up, I provide evidence for a stronger integration between carbon and energy markets in the aftermath of the EU ETS Phase I. All market correlations point to a new pricing regime with an increased dependency between EUA prices and energy prices in Phase II. The stabilized relationship indicates that energy market fundamentals become more important in the EUA price formation. Given that the theoretical allowance price should accurately reflect marginal abatement costs, the stronger price linkages are an indication that the EU ETS sets the right incentives to market participants for a cost-efficient reduction of emissions. I attribute the emergence of the new correlation regimes to the improved institutional framework and information processing of the EUA derivatives markets. In other words, the stabilized market dynamics indicate that changes in the EU ETS market structure prove effective. Diaz-Rainey et al. (2011) also argue that market integration increases due to technological change facilitating greater fuel substitution and continued liberalization policies such as EU's third energy package. But, it is questionable whether my sample is large enough to capture long-term trends.

Furthermore, the timing of shifts in correlations is interesting. The carbon-gas and carbon-electricity transition patterns suggest that the tendency towards greater market integration already evolves gradually in the course of 2007, which is the time when market participants, inter alia, learned about the European Commission's assessment of the national allocation plans for the second trading period (European Commission, 2006) that paved the way to major changes of the EU ETS. The early adjustment to new correlation regimes can be attributed to the fact that efficient carbon markets should move in anticipation of future events and that forward-looking investors already factor in the expected changes of the EU ETS in Phase II prior to its official introduction. In rebuttal, my results for the carbon-coal link indicate that it took some time until Phase II changes catch on to correlations in April 2008. From a methodological point of view, the identification of great variations in the date and pace of structural change emphasizes the advantages of a model that endogenously determines change points in correlations.

5.2.3 Carbon-financial market correlation

[Figure 2 about here]

Turning to the financial market group, carbon-stock as well as carbon-bond correlations transition on VSTOXX index, indicating integration with wider financial market conditions. But, the effect of uncertainty on the two market correlations is directly opposed and more pronounced for the carbon-stock link. While correlations between carbon and stock markets are insignificant (at -0.04) during periods of low expected stock market volatility, they rise dramatically to a correlation state of around 0.36 when the VSTOXX index climbs to higher levels exceeding c=24.84. Here, the transition between the correlation regime is smooth due to a moderate γ-value and correlations spend most of the time between the extreme states. The low correlation state prevails only in about 38% of the observations, clustering mainly in Phase I. By comparison, carbon-bond correlations switch stepwise to significantly stronger negative correlations (around -0.26 from -0.01) rather than positive correlation in episodes of high VSTOXX levels. This direction of change in the correlations is opposite to all other bivariate models.

Yet, notice the striking commonality in the timing of correlation variations, specially, with respect to extreme crisis events (see Figure 2). Overall, my results depict that times with stronger carbon-stock co-movements are also times with weaker carbon-bond co-movements. In particular, both correlation states that correspond to turbulent periods peak around the Lehman Brothers failure and then persist until around mid 2009. In the preceding period, notably the time span between the unfolding US subprime crisis in July 2007 and September 2008, I observe frequent switches between the extreme correlation states which are concentrated around the collapse of Bear Stearns in March 2008 and the failure of IndyMac Bank in July 2008.[9] The same strong temporal commonality in the co-movement variations apply to the carbon-oil link. The findings indicate that the ultimate depressive effect of the financial crisis occurs with a delay on these market linkages.[10] The delayed adjustment to the crisis is in line with Chevallier (2011) who identifies a strong episode of carbon price volatility during October 2008.

Two facts may help understand the economic rationale behind the correlation behavior. First, until the failure of Lehman Brothers on September 15, 2008, the crisis had been severe, but largely contained within the financial sector of the economy. However, in the aftermath of the collapse, it became apparent that the subprime crisis would permeate the real economy and sharply slow down economic growth (see, e.g. Caballero et al., 2008). This caused a decrease in industrial production and energy demand, curbing the demand for carbon allowances, which fostered incentives to sell EUAs. Second, as a consequence of the credit-constrained economic environment in the course of the crisis, funding needs of companies increased and selling EUAs was a proper strategy in order to obtain the cash needed (Kossoy and Ambrosi, 2010). Thus, EUA prices plummeted just as stock prices did and the joint downward price movements during the financial crisis boil down to the higher correlation regime. This finding indicates that the market mechanism of the EU ETS accurately reflects expectations for the amount of abatement required to meet emission caps under an altered macro-economic scenario. On the other hand, the negative carbon-bond correlation observed during the financial crisis may be ascribed to a broader "flight-to-quality" phenomenon, where increased risk perception induces investors to flee risky assets in favor of bonds, inducing a price decoupling of carbon and stock price on the one hand, and bond prices on the other hand. Figure 2 further depicts that the high expected stock market uncertainty due to the European sovereign debt crisis in 2010, which affected, amongst others, Greece and Ireland, again has a crucial impact on market linkages with more negative carbon-bond and more positive carbon-stock correlations.

[9] Note that both Lehman Brothers and Bear Stearns had been active players in the European carbon market (Kossoy and Ambrosi, 2010).

[10] Recall that the first interest rate cut by the US Federal Reserve in July 2007 is mostly viewed as the start of the subprime crisis.

One way of illustrating the functioning of the STCC GARCH models is to plot the conditional covariance (H_t in Eq. 3) between carbon and financial market against unexpected price shocks in the markets (ε_t in Eq. 2) from the last period. This is done separately for times of distress and calm periods via the use of covariance news impact surfaces (NIS) developed by Kroner and Ng (1998).[11] Figure 3 plots the NIS on a shock grid of [-2,2] during periods of extreme high volatility (VSTOXX=35) and extreme low volatility (VSTOXX=15). As expected, the curvature of both surfaces become steeper during high VSTOXX states, due to the higher (lower) level of carbon-stock (carbon-bond) correlations. Thus, large carbon and stock (bond) market shocks, regardless of their signs, are associated with higher (lower) conditional covariance. On the contrary, the surfaces are fairly flat during low VSTOXX states, indicating a muted effect of news on covariances in calm periods. However, it is worth pointing out the opposite reaction of carbon-stock covariances on shocks in low volatility periods: large carbon and stock market shocks, regardless of their sign, are now associated with slightly lower covariances. Notice also the different shape of the two NIS for the covariance in both volatility states. While the carbon-stock surface is clearly bowl-shaped, the carbon-bond surface is, to some degree, U-shaped along the axis for carbon market return shocks. This suggests that shocks in the bond market have only a modest impact on the covariance, which stands in contrast to the stock market shocks.

[Figure 3 about here]

In summary, my results provide strong evidence for the existence of a link between carbon and financial markets. This is in stark contrast to the influential papers of Chevallier (2009), Daskalakis et al. (2009) and Hintermann (2010) that document a market segmentation. Indeed, the degree of price linkages heavily depends on market uncertainty conditions and is exacerbated during the recent financial crisis. In times of distress, when market players expect high volatility, common macroeconomic shocks connect the markets, while they are segmented in calm periods. The VSTOXX index is a useful state variable that is informative about the uncertainty or risk of common shocks often associated with extreme crisis events that shift correlations. In this respect, the results are also significant for investors seeking for portfolio diversification. EUAs would offer diversification benefits to investors in traditional asset classes when correlations are low and remain low during periods of market turbulence. As this is apparently not the case for the carbon-stock link, the diversification potential of EUAs to equity market investors is much weaker than believed (Mansanet-Bataller and Pardo, 2008). In contrast, an investor holding a portfolio with longer-term governmental bonds might benefit from introducing EUAs to her investment set.

[11] The NIS of conditional covariances are a function of the two conditional variances and the conditional correlations, which, in turn, are a function of the transition variable, namely the the lagged VSTOXX index. For a formal presentation, see Silvennoinen and Teräsvirta (2005). To calculate the surfaces, I also fix the GARCH effects at the unconditional values.

6 Conclusion

In this paper I investigate how linkages between the EUA price and market fundamentals vary over time. My multivariate GARCH approach is designed to accommodate, for the first time, the different behaviors of correlations in times of distress compared to calm periods and the presence of structural breaks in correlation patterns, often triggered by policy events or institutional changes. I present evidence favoring closer carbon and energy price linkages in the second phase of the EU ETS. I document clear upward shift in the level of overall correlations which translate into carbon-coal(gas) correlations that are four (three) times as high in Phase II as in Phase I. Also carbon-electricity correlations climb to levels almost twice as high. I attribute the emergence of the new correlation regimes to the improved institutional framework and information processing of the EUA market. The stronger price linkages are an indication that energy market fundamentals become more important in the EUA price formation, which would have an positive effect on the cost-efficiency of the EU ETS. In contrast to previous studies, another important finding of my analysis is that carbon and financial markets are not segmented. Rather, correlations heavily depend on market conditions. In particular, high expected stock market volatility shifts carbon-stock correlation significantly upwards.

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Figure 1: Conditional correlations between carbon and commodity futures

The figure shows estimated conditional correlations from the fitted bivariate (D)STCC GARCH models listed in Table 3.

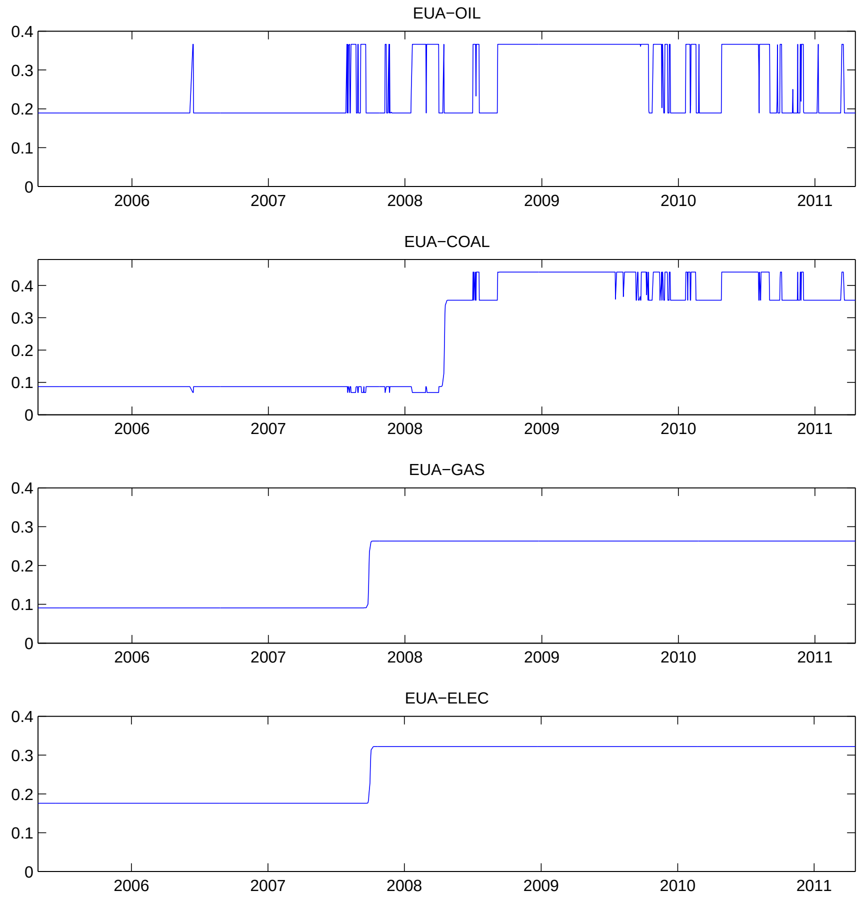

Figure 2: Conditional correlations between carbon and financial assets

The figure shows estimated conditional correlations from the bivariate STCC GARCH models when the transition variable is the one-day lag VSTOXX index, see Table 3. The red lines indicate extreme crisis events.

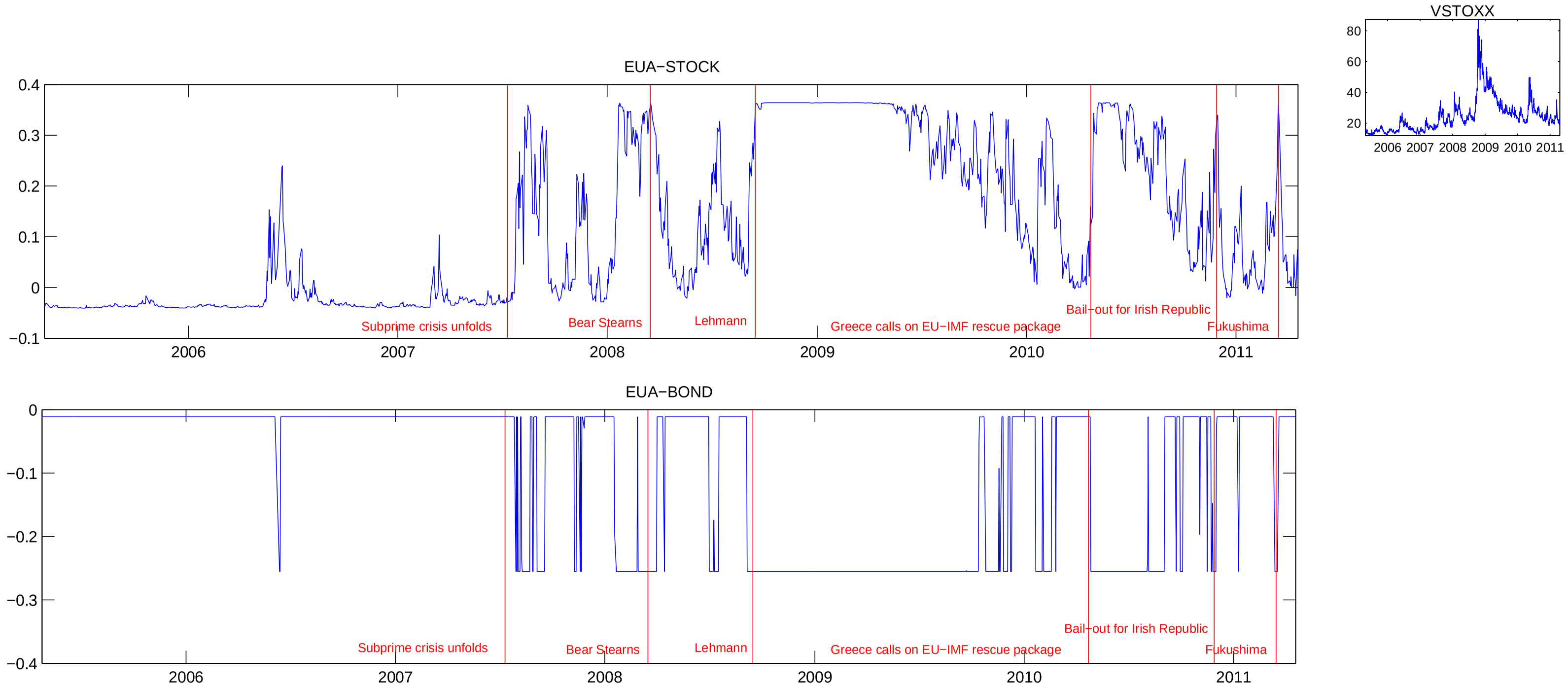

Figure 3: News impact surfaces for covariances

The figure displays the estimated news impact surfaces for the covariance between (i) carbon and stock return shocks (top) and (ii) carbon and bond return shocks (bottom) under the bivariate STCC GARCH models when the transition variable is the one-day lagged VSTOXX index. On the left hand side the transition variable is fixed to a value that indicates extreme high stock market volatility; on the right hand the transition variable is fixed to a value that indicates extreme low volatility.

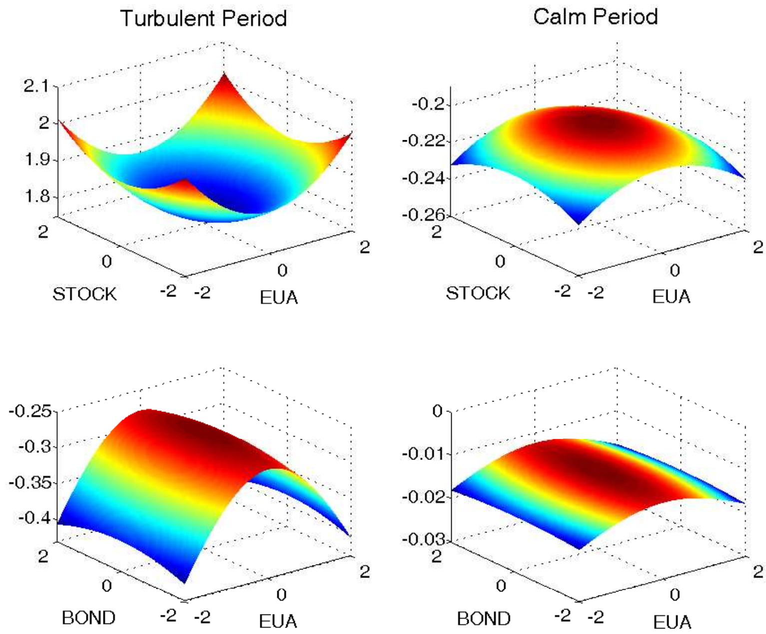

Table 1: Summary statistics of the data

Panel A presents descriptive statistics of daily returns for EU Allowance futures (EUA), Brent crude oil futures (OIL), UK natural gas futures (GAS), API 2 coal futures (COAL), UK baseload electricity futures (ELEC), EURO STOXX 50 index (STOCK), 10-year government bond index (BOND) and Certified Emission Reduction futures (CER). Panel B reports test statistics of the Augmented-Dickey-Fuller (ADF) and Kwiatkowski, Phillips, Schmidt and Shin (KPSS) tests. Panel C presents test statistics for the presence of autocorrelation and ARCH effects. AC LM is a Lagrange Multiplier test with a heteroskedasticity robust estimator for testing the null of no serial correlation up to a lag length of 5 and 20. The ARCH LM test is based on Engle (1982) and implemented as a regression of squared residuals on lagged squared residuals (1 and 10 lags). The sample period is from April 22, 2005 to April 21, 2011. * and ** denote significance at 5%, and 1%, respectively.

	EUA	OIL	COAL	GAS	ELEC	STOCK	BOND
Panel A: Descriptive statistics							
Mean[a]	-0.13	13.38	10.59	10.28	8.52	-0.22	0.69
Std. Dev.[a]	42.27	33.69	28.52	73.15	50.91	24.22	5.67
Minimum	-28.82	-10.24	-10.82	-26.28	-24.28	-8.21	-1.52
Maximum	18.65	12.64	8.32	47.77	34.08	10.44	1.61
Skewness	-0.97	0.09	-0.68	2.63	1.92	0.07	0.07
Kurtosis	15.95	5.89	8.60	22.40	22.98	10.46	4.34
Jarque-Bera (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel B: Stationarity							
ADF	-10.31**	-8.40**	-32.66**	-24.09**	-6.01**	-18.53**	-27.74**
KPSS	0.04	0.11	0.14	0.06	0.08	0.14	0.07
Panel C: Autocorrelation and ARCH tests							
AC LM(5)	11.17*	2.92	20.75**	10.67	8.48	6.60	8.06
AC LM(20)	33.84*	24.93	32.08*	25.51	21.12	13.40	19.44
ARCH LM(1)	7.36**	5.71*	12.64**	2.96	4.76*	5.00*	16.93**
ARCH LM(10)	26.35**	44.29**	29.66**	10.94	18.08*	30.31**	61.56**

[a] Mean returns and standard deviations are given in annualized percentage points.

Table 2: LM test results

This table reports the statistics and corresponding *p*-values from bivariate tests of constant correlations against a STCC GARCH model (LM_{CCC}) and from bivariate tests of a STCC against a DSTCC GARCH model (LM_{STCC}). The transition variables in the tests are calendar time (t/T) and the one-day lag of the VSTOXX index ($\mathrm{VSTOXX}_{t\text{-}1}$). The p-values listed in bold type indicate the selected most relevant transition variable(s) for each bivariate asset combination.

	t/T		$\mathrm{VSTOXX}_{t\text{-}1}$		$\mathrm{VSTOXX}_{t\text{-}1}$ and t/T		t/T and t/T	
	$\mathrm{LM}_{\mathrm{CCC}}$	p-value	$\mathrm{LM}_{\mathrm{CCC}}$	p-value	$\mathrm{LM}_{\mathrm{STCC}}$	p-value	$\mathrm{LM}_{\mathrm{STCC}}$	p-value
EUA-OIL	13.6318	0.0035	19.8526	**$8\mathrm{x}10^{-6}$**	0.2163	0.6419	10.9683	0.0009
EUA-COAL	30.1360	$4\mathrm{x}10^{-8}$	32.4736	$1\mathrm{x}10^{-8}$	10.9943	**0.0009**	0.2289	0.6323
EUA-GAS	10.5969	**0.0011**	2.1383	0.1437	-	-	3.2673	0.0707
EUA-ELEC	8.8783	**0.0029**	0.1925	0.6608	-	-	0.2271	0.6337
EUA-STOCK	11.9488	0.0005	41.2401	**$1\mathrm{x}10^{-10}$**	2.5282	0.1118	4.9377	0.0263
EUA-BOND	5.8607	0.0155	25.8439	**$4\mathrm{x}10^{-7}$**	0.0490	0.8248	9.6185	0.0019

Table 3: Selected smooth transition conditional correlation model

This table reports estimated parameter values for preferred smooth transition conditional correlation models which depend on transition variable s_i. c_i is the threshold parameter that determines the location of the transition, and γ_i determines the speed of transition. *Date* is the day that corresponds to c_i when $s_i = t/T$. With one transition variable conditional correlations move between $P_{(11)}$ and $P_{(21)}$ depending on the transition variable s_1: when $s_1 < c_1$, the correlations are closer to the state in $P_{(11)}$ than in $P_{(21)}$, and when $s_1 > c_1$ the situation is opposite. With two transition variables, $P_{(12)}$ and $P_{(22)}$ are two additional correlation states at the sample end when $t/T > c_2$. Again, s_1 drives the correlation between the two added matrices. Values in parentheses are Bollerslev-Wooldridge QML standard errors.

	s_1	s_2	$P_{(11)}$	$P_{(21)}$	$P_{(12)}$	$P_{(22)}$	c_1	c_2	γ_1	γ_2	*Date*
Panel a											
EUA-OIL	$VSTOXX$		0.189	0.366			25.454		500		
			(0.031)	(0.035)			(0.819)		(.)		
EUA-COAL	$VSTOXX$	t/T	0.087	0.069	0.354	0.441	26.082	0.494	500	500	17-Apr-2008
			(0.037)	(0.129)	(0.050)	(0.036)	(0.177)	(0.003)	(.)	(.)	
EUA-GAS	t/T		0.088	0.255			0.386		29.801		22-Aug-2007
			(0.033)	(0.040)			(0.046)		(42.595)		
EUA-ELEC	t/T		0.176	0.322			0.404		500		02-Oct-2007
			(0.034)	(0.033)			(0.026)		(.)		
Panel b											
EUA-STOCK	$VSTOXX$		-0.042	0.364			24.838		4.773		
			(0.051)	(0.046)			(1.601)		(2.438)		
EUA-BOND	$VSTOXX$		-0.011	-0.255			25.415		500		
			(0.033)	(0.038)			(0.657)		(.)		