Energy 88 (2015) 417–429

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Energy markets and CO_2 emissions: Analysis by stochastic copula autoregressive model

Vêlayoudom Marimoutou, Manel Soury*

Aix-Marseille University, (AMSE), CNRS, EHESS, 2 rue de la Charité, 13002 Marseille, France

ARTICLE INFO

Article history:
Received 12 October 2014
Received in revised form
20 April 2015
Accepted 18 May 2015
Available online 29 June 2015

Keywords:
CO_2 emissions
Dependence
SCAR copula
Efficient importance sampling
GAS model

ABSTRACT

We examine the dependence between the volatility of the prices of the carbon dioxide "CO_2" emissions with the volatility of one of their fundamental components, the energy prices. The dependence between the returns will be approached by a particular class of copula, the SCAR (Stochastic Autoregressive) Copulas, which is a time varying copula that was first introduced by Hafner and Manner (2012) [1] in which the parameter driving the dynamic of the copula follows a stochastic autoregressive process. The standard likelihood method will be used together with EIS (Efficient Importance Sampling) method, to evaluate the integral with a large dimension in the expression of the likelihood function. The main result suggests that the dynamics of the dependence between the volatility of the CO_2 emission prices and the volatility of energy returns, coal, natural gas and Brent oil prices, do vary over time, although not much in stable periods but rise noticeably during the period of crisis and turmoils.

1. Introduction

Under the Kyoto protocol, OECD countries must reduce their emissions of greenhouse gas by a minimum of 5% from 1990 levels during the period 2008–2012. In this framework, the European Union has decided to reduce CO_2 emissions by 8%. To do that, the EU has proposed a framework scheme known as the EU-ETS (European Union Emission Trading Scheme) to determine the price of CO_2 (carbon dioxide) emissions. In this context, european plants with large CO_2 emissions obtain from their governments allowances to emit metric tonnes of CO_2 equivalent. Permits can be traded in spot, future and option markets. In the european context, the first phase of trading was in the years 2005–2007 and the second one was in the years 2008–2012 coinciding with the introduction of the Kyoto protocol. The third trading phase started in 2013 and will last until December 2020. In the European Union, the higher production of carbon dioxide emissions is concentrated on the power generation sector and on the small number of plants. The power sector and the heat generation industry drive approximately 55% of the total allowance in the first phase and thus are the key players in the EU-ETS and their behavior greatly influences the carbon price dynamics. The purpose of the EU-ETS trading scheme is to encourage firms to reduce their emissions. For Paolella and Taschini (2008) [2] the scarcity of allowances will drive-up the trend in prices. However, the short life of the prices of CO_2 emissions is associated with a large level of uncertainty. The price of carbon is usually determined by the market structure and institutional policies. The level of emissions depends on unexpected movements in energy demand, the prices of oil, gas, coal, … and weather conditions (temperatures, rainfall, …). Bredin and Muckley (2011) [3] show that this market is driven by its fundamental variables, and can be affected by economic growth and/or financial markets. So what are the factors that determine the price of CO_2? In a survey, Springer (2003) [4], shows that among the cofactors that determine the CO_2 emission allowance prices, energy prices and climatic conditions are fundamentals. The main drivers of the price of carbon can be categorized as factor driver by demand and supply forces. Thus, the key supply factors are the number of emission allowances, allocated to individual installations in the National Allocation Plans by the EU, as well as other regulatory uncertainties. The demand factor, however, is more dynamic and the allowance demand is strongly influenced by the demand for electricity. As a result, factors that influence the demand for electricity, such as (extreme) temperature, seasonality and general economic activity are also thought to drive the demand for carbon emission allowances. In the recent literature about the empirical relationship between European Union Allowances prices and its fundamentals,

* Corresponding author.
E-mail addresses: velayoudom.marimoutou@univ-amu.fr (V. Marimoutou), manel.soury@yahoo.fr (M. Soury).

http://dx.doi.org/10.1016/j.energy.2015.05.060
0360-5442/

a large theoretical review of the determinants was made by Springer (2003) [4]. Christiansen et al. (2005) [5] identifies economic growth, energy prices and weather conditions as key drivers of EUA prices. Chevallier et al. (2008) [6] found that the industrial production impact positively (negatively) the carbon market during periods of economic expansion (recession), confirming the relationship between macroeconomics and the price of carbon. (Burniaux (2000) [7], Ciorba et al. (2001) [8], Sijm (2005) [9] and van der Mensbrugghe (1998)) in the same way showed that energy prices influence CO_2 prices. Redmond and Convery (2007) [10], Bataller et al. (2013) [11], Alberolaa et al. (2008) [6] and all studies including energy variables, assumed geometrical brownian motion process for modeling energy prices. To model electricity, natural gas spot prices, commodity prices, or to describe energy commodities, we use a geometric brownian motion with mean reversion in a long term value θ in the drift term. Concerning the stochastic volatility model, Eydeland and Geman (2005) [12] extend the Heston model (1993) [13] to gas and/or electricity prices. The movements in price are, however, not independent. If they were, then it would be possible to form a portfolio with negligible volatility. To understand the relative magnitude of all these correlations and why they change, it is important to look at the economic factors behind the movements in asset prices. Changes in asset prices reflect changing forecasts of future payments. The information that changes the forecasts is often called "news". Every element of news affects all asset prices; this is one of the most important reasons why correlations change over time. The second important reason is the characteristics of the news change. Time variations arise only from substituting volatility in the innovation for dividends. If there is no predictability in expected returns, then this is also the conditional variances of returns. The longer the memory of the dividend process, the more important is this effect and the greater is the volatility. For these energy commodities, the price is strongly time dependent, and consequently, the covariance and the unconditional correlation are time dependent as well.

We examine, in this paper, the dependence between the conditional volatility of the prices of CO_2 emissions with the conditional volatility of their fundamentals (energy prices): coal, natural gas and Brent Oil as well as the SP-GSCI energy price. We focus on energy because it is used in industrial production and activities with high fossil fuel consumption, and consequently have large CO_2 emissions and as energy prices are one of the main factors determining and driving the carbon prices as stated above. The dependence between the returns will be approached by a particular class of dynamic copula, the SCAR (Stochastic Autoregressive) Copulas, a time varying copula that was first introduced by Hafner and Manner (2008) [1] in which the parameter driving the dynamics of the copula follows a stochastic autoregressive process and takes into account the non linearity of the data. In this copula the parameters of volatilities and dependence are estimated by standard maximum likelihood together with Efficient Importance Sampling.

Our article contributes to the literature in several important aspects. We use the dynamic SCAR copula approach to examine the relationship over time between the variables in pairs. In other words, we examine the dynamics of the correlation or dependencies in term of conditional volatility pair by pair between the carbon dioxide emission prices and the other energy prices: (CO_2/Brent oil, CO_2/Natural Gas, CO_2/SP energy index and the CO_2/coal). We used the dynamic SCAR copula approach, the choice of the best fitted copula model, presented as follows, for each pair mentioned above, respectively, is based on the log-likelihood criteria: the rotated Gumbel copula, the Gumbel, the Normal copula and the Frank copula. We have observed for the last pair a strong correlation and common movement, after mid-2011, in the level of trends (obtained by a decomposition analysis in state space framework (see Fig. A3 in Annex). In addition it is important to mention the fact that since the CO_2 emission prices are traded essentially in European countries, our variables concern also the European markets, except the Natural Gas that is traded in the American market. However we have kept it since it does not differ from the evolution of Natural Gas prices in European countries. Copulas are a flexible, non-standard tools that help decomposing any multivariate distribution into marginal distributions, that describe individual behavior, and fully capture the dependence between the variables. The fact that dependencies can be modeled independently of the marginal distributions, contributed to the expansion of this approach especially since it can be applied over the various type of data and not only financial ones. By focusing on the particular case of the dynamic type of copula, we have improved our model further, since investigating the dependence structure between the commodities and CO_2 emission prices through time is much more realistic and efficient than doing it in a static way. In this context, we find some papers that used the copula approach either in its static version or its dynamic one introduced by Patton, with different commodities. However, in our knowledge, this is the first paper to deal with the implication of energy price commodities on CO_2 emission prices by means of the dynamic SCAR copula. To the best of our knowledge, copulas have been used in commodities markets by Zohrabyan (2014) [14], Kharoubi and Geman (2008) [15], Reboredo (2011) [16], Nguyen and Bhatti (2012) [17], Hammoudeh et al. (2013) [18] and Syed et al. (2014) [19]. In addition, the returns of the series are modeled by the GAS (Generalized Autoregressive Score) model that can deal with the jumps, and occasional and temporary changes in the returns better than the GARCH-type model and thus lessens the impact of occasional extreme observations in the series. With the GAS model, the time-varying parameter which characterizes the conditional distribution can be updated using the scaled score of the likelihood function. In section two we present the model and the estimation method used; in section three, the empirical results will be presented and discussed before concluding.

2. The model

2.1. The SCAR model

We introduce the SCAR (Stochastic Copula Autoregressive) model proposed by Hafner and Manner (2012) [1], that can be seen as a multivariate stochastic volatility model. We consider the bivariate time series $(u_{1,t}, u_{2,t})$ for $t = 1 \ldots T$ distributed using a time varying copula C with a dynamic parameter θ:

$$(u_{1,t}, u_{2,t}) \propto C(u_1, u_2 | \theta_t) \tag{1}$$

where $\theta_t \in \Theta \subset \mathbb{R}$. We suppose that θ_t is driven by a latent stochastic process where $\theta_t = \Psi(\lambda_t)$ and $\Psi : \mathbb{R} \to \Theta$ is a predefined function to assure that the copula parameter is defined in its own domain, depending on the chosen copula.[1] λ_t is an unobservable underlying process that follows a first order autoregressive process:

$$\lambda_t = \alpha + \beta \lambda_{t-1} + \kappa \varepsilon_t, \quad |\beta| < 1, \quad \kappa > 0 \tag{2}$$

with ε_t is a Gaussian innovation process. The observed variables are transformed into uniform distribution. In the SCAR copula the dynamics are not generated by the data/observations as in the

[1] For Frank copula the transformation Ψ is $\Psi(x) = x$, for the Clayton copula, it is $\Psi(x) = \exp(x)$, for the Gumbel copula $\Psi(x) = exp(x) + 1$ and for the Gaussian, the Ψ is the inverse Fisher transform, $\Psi(x) = \exp(2x){-}1/\exp(2x) + 1$.