Economic Modelling 36 (2014) 229–234

Contents lists available at ScienceDirect

Economic Modelling

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

Volatility spillovers between the oil market and the European Union carbon emission market

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ARTICLE INFO

Article history:
Accepted 24 September 2013
Available online xxxx

JEL classification:
C22
C58
G11
G15
G32
Q52

Keywords:
CO_2 emission allowances
Oil prices
Volatility spillovers
Range volatility

ABSTRACT

This paper examines the dynamics of volatility transmission between EU emission allowances (EUA) and oil markets using a range-based volatility measure. We propose a multivariate conditional autoregressive range model with bivariate lognormal distribution to capture volatility dynamics and volatility spillovers between oil and EUA markets. Our findings for Phase II of the European Union Emissions Trading Scheme point to the existence of volatility dynamics and leverage effects and to no significant volatility spillovers between these markets. These results remained robust to other volatility measures and model specifications.

1. Introduction

This article examines the dynamics of volatility transmission between the European Union allowances (EUA) market and the oil market. Exploring the extent to which volatility shocks in oil markets are transmitted to carbon markets or vice versa is of great importance to investors, policy makers and researchers. The joint behaviour of volatility is paramount for the construction of portfolios and for asset pricing – particularly for derivatives – and is also essential for risk management, as it determines the benefits of diversification, the optimal hedge ratio against risk and the value-at-risk measure. In addition, EUA volatility and volatility transmission between the EUA and oil markets are of interest to regulators, given that the impact on prices of carbon emission control policies is linked to EUA volatility (see, e.g., Daskalakis and Markellos, 2009) and the factors affecting that volatility, in particular, oil price volatility. Likewise, consideration of volatility transmission is essential to making efficient econometric inferences and accurate forecasts of volatility in both markets.

Oil prices have traditionally been more volatile than the price of other tradable commodities; furthermore, their volatility has been found to have negative effects on investment (Elder and Serletis, 2010), growth (Ferderer, 1996), stock market returns and returns volatility (see, e.g., Arouri et al., 2011; Reboredo, 2010; Reboredo and Rivera-Castro, 2013; Sadorsky, 1999; Vo, 2011). Although oil and EUA markets are linked at the theoretical and empirical level (see Kanen, 2006; Reboredo, 2013; Redmond and Convery, 2006), and although EUA have become a tradable asset – negotiated in organized financial markets that have steadily increased in liquidity and trading volume since the European Union emission trading scheme (EU ETS) was implemented – no study has as yet explored the extent to which oil price shocks are transmitted to current and future volatility in carbon markets or vice versa.[1]

Previous studies have examined the transmission of volatility in financial markets from different perspectives. Using return-based volatility measures, Engle et al. (1990), King and Wadhwani (1990), Cheung and Ng (1996) and Hong (2001) developed tests for volatility spillover effects in a range of stock and exchange rate markets. For the oil market, Arouri et al. (2011) and Vo (2011) studied volatility transmission between oil and stock markets using the multivariate generalized autoregressive conditional heteroskedasticity (GARCH) and stochastic volatility models, respectively. From a different perspective, Diebold and Yilmaz (2009) measured the magnitude of return and volatility spillovers through variance decomposition of forecasted error variances in a vector

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[1] Volatility spillovers in the EU ETS between spot and future prices have been analysed by Joyeux and Milunovich (2010) and Rittler (2012). Volatility instability of carbon prices has been studied by Chevallier (2011).

0264-9993/$ – see front matter
http://dx.doi.org/10.1016/j.econmod.2013.09.039

autoregressive model. Given that, compared to other volatility measures, the return-based volatility measure suffers from informational inefficiency; another strand of the literature has focused on volatility transmission by considering realized volatility or range-based volatility. Bubák et al. (2011), for example, analysed volatility transmission in emerging European foreign exchange markets using realized volatility and a dynamic version of the Diebold–Yilmaz approach. Diebold and Yilmaz (2012) studied volatility spillovers across US asset markets using range-based volatility estimates and an improved version of the volatility spillover index developed in Diebold and Yilmaz (2009). Chiang and Wang (2011) studied volatility contagion in financial markets due to the subprime crisis using the volatility-range measure and a smooth transition copula function.

In this paper, we adopt the volatility-range measure since it has better properties than the return-based volatility estimate in terms of measurement errors (Parkinson, 1980), efficiency and robustness to market microstructure noise (Alizadeh et al., 2002) and in-sample and out-of-sample volatility forecasts (Brandt and Jones, 2006). Also, Christensen and Podolskij (2007) and Martens and van Dijk (2007) showed that the range-based estimate of integrated volatility is more precise and robust to market microstructure noise than the return-based estimate. We examine volatility spillovers between the EUA and oil markets by extending the conditional autoregressive range model (CARR) proposed by Chou (2005) to a multivariate time series specification. The multivariate CARR (MCARR) model provides the conditional volatility dynamics for EUA and oil price series as well as the conditional cross-effects between them. We also considered leverage effects and different conditional correlation specifications so as to take into account volatility interdependence. Within the MCARR model we formally tested for: (1) volatility spillovers, by running a simple coefficient test similar to \kern-2pt\lower2ptthe Granger causality test, and (2) conditional contemporaneous dependence and time-varying dependence using the likelihood ratio test. This approach is fundamentally different from the one adopted by Chiang and Wang (2011), who considered the CARR model to study volatility contagion using a smooth transition copula that captures interdependence but which is not capable of capturing volatility spillovers.

Our empirical study of volatility transmission was conducted from the onset of Phase II of the EU ETS in 2008, since this phase is featured by a more stable relationship between the EUA price and its determinants (Bredin and Muckley, 2011) and by a significant rise in market liquidity in EUA future markets (Benz and Hengelbrock, 2008; Bredin et al., 2009). By analysing weekly data for EUA future contracts and crude oil price volatilities, our study makes two major contributions to the empirical literature on modelling oil and carbon emission linkages. Firstly, as far as we are aware, ours is the first study to investigate EUA and crude oil market volatility spillovers and interdependence and provides empirical evidence of no spillover effects and volatility independence. Oil price volatility, therefore, plays no role in explaining the time dynamics in the conditional volatility of EUA prices and is of no value in forecasting future EUA price volatility. Secondly, our research contributes to the literature on spillover effects by considering the CARR model in a multivariate context, taking into account different dependence specifications for conditional dependence and asymmetric effects.

The rest of the paper is laid out as follows: Section 2 provides a brief overview of the EU ETS. Section 3 introduces the multivariate CARR model developed to capture volatility spillovers between the EUA and oil markets. Sections 4 and 5 present data and results, respectively. Finally, Section 6 provides the conclusions of the paper.

2. The European Union Emissions Trading Scheme

The EU ETS was launched in January 2005 as a market-based approach to combatting greenhouse gas emissions that rewards the reduction of carbon emissions with economic incentives. The system is organized in three commitment phases: Phase I (2005–2007), the pilot phase; Phase II (2008–2012), coinciding with the first Kyoto protocol commitment to reduce greenhouse gas emissions by 8% below the 1990 level in the EU; and Phase III, to cover the period 2013–2020. Currently obliged to participate are four industrial sectors: energy, ferrous metals production and processing, the mineral industry and other energy-intensive activities. One EUA unit grants the holder the right to emit one metric tonne of CO_2-equivalent (tCO2e) during a specified commitment phase.

The market is structured as a cap-and-trade system. Participating installations are allocated a specific volume of EUA, currently determined according to a national allowance plan (NAP) approved by the EU Commission that specifies the total number of allowances assigned to a member state and the rules for distribution among participating installations. Participating installations can either consume their stock of EUA by emitting CO_2 or reduce emissions and sell off their surplus EUA; installations that lack EUA can purchase them (privately, over the counter or in a climate exchange). Participating installations report their emissions and return the equivalent quantity of EUA to their government on the 30th day of April each year. Installations can also use Kyoto protocol trading emission system instruments called certified emission reductions (CERs), obtained for emission reduction projects, or emission reduction units (ERUs), obtained by reducing emissions under what are called Joint Implementation projects. Emissions not covered by any of these systems are fined at the rate of 40 (Phase I) or 100 (Phase II) euros/tCO2e.

Climate-exchange or over-the-counter trading is regulated by member states and supervised by national authorities. BlueNext in Paris and ICE Futures in London are the most liquid spot market and futures market, respectively, accounting for around 70% and 90% of the daily turnover in their respective markets.

3. The multivariate conditional autoregressive range model

Parkinson (1980) showed that the range of log prices at time t, defined as $R_t = \max\{P_\tau\} - \min\{P_\tau\}$, where $\tau \in [t-1, t]$, is an unbiased estimate of price volatility (measured by the standard deviation). To capture temporal dependence in price volatility, Chou (2005) proposed the CARR model of lag order p and q specified as follows:

$$R_t = \lambda_t \varepsilon_t, t = 1, \ldots, T, \tag{1}$$

$$\lambda_t = \omega + \sum_{i=1}^{p} \alpha_i R_{t-i} + \sum_{j=1}^{q} \beta_j \lambda_{t-j} \tag{2}$$

where λ_t is the conditional expected range at time t given the information set, I_{t-1}, up to time $t-1$, and where ε_t is the disturbance term with mean one and a density $f(\varepsilon_t;\theta)$ defined over $[0,\infty)$ with a parameter vector θ. To ensure that λ_t is positive, the coefficients $(\omega,\alpha_1, \ldots,\alpha_p,\beta_1, \ldots,\beta_q)'$ in Eq. (2) must be nonnegative. The CARR model can be easily extended to consider exogenous variables in Eq. (2).

Although Chou's (2005) study considered the exponential and Weibull density functions for the disturbances, Alizadeh et al. (2002) proved that log price ranges follow a normal distribution; meanwhile, Brandt and Jones (2006) showed the superiority of the range-based volatility model with lognormal disturbances over the return-based volatility model. We thus consider the lognormal distribution for the disturbance terms, $\varepsilon_t | I_{t-1} \overset{i.i.d.}{\sim} LN(-\sigma^2/2, \sigma^2)$, specified as:

$$f\left(\varepsilon_t; \sigma^2 \middle| I_{t-1}\right) = \frac{1}{\varepsilon_t \sqrt{2\pi\sigma^2}} \exp\left(-\frac{\ln(\varepsilon_t) + \left(\sigma^2/2\right)^2}{2\sigma^2}\right) \tag{3}$$