Biodiesel as a motor fuel price stabilization mechanism

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Abstract

This article studies the capacity of biofuels to reduce motor fuel price fluctuations. For this purpose, we study dependence between crude oil and biodiesel blend prices in Spain. Copula models are used for this purpose. Results suggest that the practice of blending biodiesel with diesel can protect consumers against extreme crude oil price increases.

Keywords: biodiesel, crude oil, dependency analysis, copula models.

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1. Introduction

The European Union (EU)'s transportation sector, which represents around a third of EU's final energy consumption, is facing several challenges including contribution to local air pollution and global warming and strong dependence on fossil fuels. While biofuels may play a role in mitigating these problems, the first initiatives to support biofuel production within the EU, undertaken by France and Germany by the end of the 1980s, mainly aimed at offering alternative outlets for agricultural overproduction. More recently, EU's biofuel policies have contributed to a more widespread production and consumption of biofuels within the EU and have recognized the wider range of problems that biofuels can address.

The curbing of greenhouse gas emissions, improvement in security of energy supply in the medium and longer term, reduction in the dependence on crude oil imports, or the creation of opportunities for rural economy uplifting are motivations behind public promotion of biofuels. The economic impacts of biofuels can however go beyond the agricultural sector to embrace national economies as a whole and their deficits.[1] Biofuel support instruments used around the world include subsidies, blending mandates, tariffs, tax incentives, among others. Biofuel mandates[2] and tax exemptions have been key in biofuel promotion in the EU. Supply-side policies such as development of cars that can run on high concentration or pure biofuels have, however, been more limited (Pelkmans et al., 2008).

The EU's Directive 2003/30/EC[3] was passed to promote the use of biofuels and other renewable fuels in the European transportation sector. It established that Member States should define national mandates to ensure that biofuels and renewable fuels represent a minimum proportion of the fuels market. The binding target was set at 5.75% of all petrol and diesel used for transportation purposes by December 2010. Further, the Directive established that biofuel blends above 5% should be specifically labeled to inform consumers of the biofuel content. Biofuels are usually sold blended in mineral oil derivatives. Low biofuel blends can be used to run existing motor vehicles and can be distributed using existing fuel distribution systems. This involves important savings in logistics to reach consumers and creates the potential for fast large-scale biofuel penetration.

While biofuel policies target different objectives, this article is specifically interested in the capacity of biofuels to reduce the vulnerability of the national economies in front of energy price fluctuations. Assessing this issue is specially relevant in light of the evolution of energy prices since the second half of the 2000s, characterized by marked volatility and extreme market events. The high dependence of the EU's transportation sector on fossil fuel imports makes this sector very vulnerable to crude oil market shocks (Biofuels Research Advisory Council, 2006). Further, unstable energy prices are expected to continue given the increasing demand coming from rapidly growing developing economies, limited crude oil reserves and political unrest in crude oil producing countries that can cause important supply disruption, speculation, etc. This instability can harm the whole economy (Ferderer, 1996; Vedenov et al., 2006). As has been shown by Kneller and Young (2001), oil price fluctuations and economic growth are negatively correlated. Sadorsky (1999) finds corporate stock prices to decline as a response to increased instability in fossil fuel prices. Our work aims at assessing to what extent biofuels have the capacity, relative to fossil fuels, to soften the impact derived from extreme changes in crude oil prices, which are the most likely to have harmful economic impacts. To do so, we study what is the likelihood that extreme crude oil price increases (decreases) are passed on to biofuel blend prices at the pump. Biofuel price behavior is compared with that of conventional fossil fuel.

Whereas ethanol and biodiesel are the two main liquid biofuels produced around the world, we focus on biodiesel given its relevance within the EU's biofuel market and given the importance of diesel within the European motor fuel market. More specifically, we model the dependence between two pairs of prices: crude oil and biodiesel, and crude oil and diesel in Spain, one of the most relevant EU's biodiesel producing countries.

Modeling dependence between two (or more) variables is not an easy task. While the statistics literature has proposed a wide range of univariate parametric distributions to assess univariate behavior, multivariate distributions are certainly more scarce, the normal and t-student being the most common. Most multivariate distributions often entail the restrictive property that the marginal distributions are all of the same type. Incorrect assumption of the multivariate distribution form characterizing price behavior can lead to biased parameter estimates and unreliable results. The statistical theory of copulae is, in this regard, a very powerful instrument to model joint dependence because it does not require any assumption on the multivariate distribution. By decomposing an *n*-dimensional distribution into its *n* marginal distributions and a copula, copulas allow to construct better and less restrictive dependence models (Patton, 2006).

This article is organized as follows. Section 2 presents an overview of the biofuels market in the EU and in Spain. The third section offers a literature review of analyses of price transmission in energy markets. Methodological details and research results are presented in the fourth and fifth sections, respectively. The paper ends with a concluding remarks section.

2. The biofuels market in the EU and in Spain

Ethanol and biodiesel dominate the international biofuel market. The United States and Brazil are the two largest world producers of ethanol, with a market share of 54% and 34% respectively in 2009 (Renewable Fuels Association RFA, 2011). In contrast, the international biodiesel market is dominated by the EU that concentrates around 65% of worldwide production (European Biodiesel Board EBB, 2010). Biodiesel output represents around 75% of the EU's biofuel production.[4] This is compatible with the fact that diesel is more important than gasoline within the EU's transportation sector. While bioethanol produced in the EU has been estimated to be competitive at crude oil prices above €90 per barrel, biodiesel breaks even at prices above €60 per barrel (Biofuels Research Advisory Council, 2006).

In the framework of the recent outburst of the global biofuels industry, EU's biodiesel production has experienced an important expansion from 3,184 thousand tons in 2005 (EBB, 2006) to 9,046 thousand tons in 2009 (EBB, 2010), an increase on the order of 184%. During the same period of time, Spanish production grew from 73 to 859 thousand tons. Spain represents around 10% of total EU's biodiesel production and is the third largest producer after Germany and France.

The EU's biodiesel industry is characterized by its important idled capacity. While 2009 production was on the order of 9 million tons, production capacity totaled 22 million tons distributed among 245 facilities (EBB, 2010). Spanish production capacity was on the order of 3.6 million tons, while actual production did not reach 0.9 million tons. Such a large production capacity is the outcome of the investments in biodiesel plants responding to expectations motivated by EU's promotion of the use of renewable energy through the EU's Directive 2009/28/EC (repealing Directive 2003/30/EC). The Directive, that defined a 10% target for renewable energy use in 2020, implies an increase (relative to the increase expected under the old legislation) in biofuel demand on the order of 10.8 million toe reaching 34.6 million toe in 2020 (European Commission, 2007). It is expected that second generation biofuels that involve less competition with food production, will represent around 30% of EU biofuel needs by 2020. Accordingly, several biodiesel producers are taking up positions in the development of second-generation biofuels (EurObserv'ER, 2010).

Favorable expectations for biodiesel have been more recently curved by heavily subsidized biodiesel imports from the US, imports from Argentina benefiting from an artificial mechanism of export taxes and from free access to EU markets, and by the recent economic crisis that has reduced fuel and biofuel demand (EBB, 2010; EurObserv'ER, 2010). In some member states, specially Germany, there has also been a reduction in the fiscal advantages conferred to biodiesel and in the compulsory blending mandates. These changes, coupled with an increase in feedstock costs due to recent agricultural price inflation, have harmed EU's biodiesel competitiveness and contributed to unused production capacity.

EU biofuel use for transportation reached 12 million toe in 2009, representing 4% of all fuels used in the transportation sector (300 million toe). While 2010 statistics are not yet available, the EU Directive 2003/30/EC goal for 2010 should involve a biofuel consumption on the order of 18 million toe (EurObserv'ER, 2010). Biodiesel represents almost 80% of total biofuel use. The biofuel consumption growth rate has, however, been slowing down in the last few years: from 42% between 2006 and 2007, to 19% between 2008 and 2009. While EU biofuel consumption has hindered (mainly due to a decline in Germany), growth rates in Spain are still buoyant (71% between 2008 and 2009). In 2009 Spain consumed 894 thousand toes of biodiesel and 152 thousand toes of bioethanol, being the biofuel market share of 3.4% (EurObserv'ER, 2010), the binding mandate set by the government (Orden ITC 2877/2008). This mandate has been set to 6.2% for the current 2011 year (Real Decreto 459/2011). Biodiesel blends on the order of 10%, 20% and 30% are commonly sold in Spain and benefit from favorable tax treatment as they are exempted from the hydrocarbons tax till the end of 2012 (Law 22/2005). Other policies such as fiscal incentives for biofuel pilot and industrial plants, fiscal incentives for investments in biofuel production, or support to biofuel-related R&D projects are also applied (Pelkmans et al., 2008).

Feedstocks currently used for biofuel production differ by region, but they are mainly vegetable oils. While rapeseed oil[5] is predominant within the EU as a whole, sunflower oil is the major feedstock used in Spain (Pelkmans et al., 2009). The first biodiesel plants in Spain relied on waste vegetable oils that were cheaper than pure plant oils. However, given the scarce potential of waste oils, the Plan for Renewable Energy 2005/2010 (Instituto para la Diversificación y Ahorro de la

Energía IDAE, 2005) established that the development of the biodiesel industry in the 2005-2010 period should be heavily based on pure plant oils. More than 90% of biodiesel production costs are attributed to sunflower oil feedstock costs (IDAE, 2005). As a result, the price of feedstock is essential for biodiesel competitiveness within the liquid fuels market.

3. Literature review

Several studies have addressed price transmission processes between crude oil, a global commodity whose price is determined in the international market, and refined crude oil products that are locally priced. Differences in price formation processes between these two commodity types involve that crude oil prices should determine changes in petroleum product prices and not the other way around (Borenstein et al., 1997; Pindyck, 2004). Price transmission studies have been usually based upon non-structural time series models that offer the main advantage of only requiring price data for econometric estimation. Further, most of these analyses have been based on spot or cash prices that represent the single best indicator for market conditions (Pindyck, 2004). Recent levels hit by crude oil prices have renewed the interest for studying price behavior in mineral oil derivative markets. Understanding price behavior is relevant since it affects the risk exposure of producers and consumers, the investment incentives in inventories, production, or transportation facilities (Pindyck, 2004).

The vertical price transmission literature focusing on refined crude oil products can be classified according to whether it studies price behavior in levels (price spillovers along the marketing chain), or on volatility patterns (volatility spillovers). The unpublished work by Ben Sita and Marrouch (2011) analyzes extreme volatility spillovers between crude oil spot prices and a series of mineral oil derivative prices: diesel, gasoline and heating oil. Univariate Asymmetric Power Autoregressive Conditional Heteroskedasticity (ARCH) models incorporating multivariate effects are used for this purpose. Their findings suggest that price volatility transmission between crude oil and refined products is of an asymmetric type. Hammoudeh et al. (2003) utilize symmetric Generalized ARCH (GARCH) models to assess both price and volatility spillovers between crude oil and refined product (gasoline and heating oil) prices in the US. They find evidence of strong links between these markets.

Evidence of asymmetric price spillovers is found by Borestein et al. (1997), Radchenko (2005), Chen et al. (2005), Al-Gudhea et al. (2007), Honarvar (2009), or Radchenko and Shapiro (2011) who show, by using threshold cointegration, hidden cointegration, or asymmetric error correction models, that US gasoline prices increase faster when crude oil is becoming more expensive than when it's becoming cheaper. Galeotti et al. (2003) find evidence of asymmetries in European gasoline markets by using asymmetric error correction models.[6] Another group of studies, however, has been unable to find asymmetries in the transmission of price shocks from crude oil to gasoline prices (see, for example, Godby et al., 2000 or Bachmeier and Griffin, 2003).

Different explanations for vertical asymmetric price behavior in the liquid fuels market have been proposed in the literature. These include, among others, market power and search costs. Borenstein et al. (1997) suggest that, as a result of oligopolistic coordination, an increase in input prices will be quickly transferred to consumer prices to avoid a decline in retail margins. Conversely, declines will only be passed on to consumers as a response to a threat of price cutting by competitors.

According to search costs with Bayesian updating's theory (Johnson, 2002; Benabou and Getner, 1993), consumers increase their search among gas stations when gasoline becomes more expensive. But when gasoline prices decline, search incentives decline as well. This leads to price asymmetries. Those gas stations that do not increase prices as a response to increased crude oil prices will see their demand increased, which will push their prices up. Conversely, in a gasoline price deflation context, those retailers setting higher prices will not suffer from a significant sales decline, which will reduce incentives to pass on input price declines.

More recently, a series of research papers have been published that study vertical price transmission patterns within the biofuels industry using time-series econometrics (Ciaian and Kancs, 2011; Nazlioglu, 2011; Cha and Bae, 2011; Chang and Su, 2010; Chen et al., 2010; Serra et al., 2011a and 2011b; Zhang et al., 2010; Balcombe and Rapsomanikis, 2008).[7] Though a generalization of research results is difficult to make, most of these studies suggest that the outbreak of the biofuels industry has driven food prices up and strengthened the link between food and energy prices.

Another group of related analyses aims at responding whether the introduction of biofuels can contribute to reduce fuel price levels and volatility. Du and Hayes (2009), Sexton et al. (2008) or Rajagopal et al. (2007) show a negative effect of ethanol on gasoline prices, which may induce and increase in energy consumption. The question of whether biofuels can reduce energy price fluctuations has been addressed by Tokgoz and Elobeid (2006), who suggest that ethanol blending with gasoline should reduce fuel price fluctuations. Vedenov et al. (2006) and Tareen et al. (2000), by means of using the real options approach, show biodiesel and ethanol to be less volatile than petroleum diesel and gasoline.

While the articles by Tokgoz and Elobeid (2006), Vedenov et al. (2006) and Tareen et al. (2000) offer valuable insights on the impacts of biofuels on energy price stability, they focus on a period when the outbreak of the biofuels market had not yet occurred or was just starting to take place. A more up to date analysis on this issue is thus warranted. Our work contributes to previous literature by assessing the dependence of diesel and biodiesel prices on crude oil prices during extreme market events. We aim at studying what is the price dependence during extreme upturns and downturns of the market.

4. Methodology

Univariate distributions of economic time series are usually found to be characterized by excess kurtosis, skewness and nonnormality. Further, it has also been found that related price series are likely to show asymmetric dependence, which is an indicator of multivariate nonnormality (Patton, 2006). In spite of this, most previous studies assessing price transmission within energy markets have assumed multivariate normality, which may lead to biased parameter estimates. It is also true that the range of available multivariate distributions is scarce and this limits how multivariate dependence can be modeled (Parra and Koodi, 2006).

To overcome this limitation we study the dependency between crude oil and diesel and biodiesel prices using Sklar's (1959) theorem. The theorem shows that an *n*-dimensional joint distribution characterizing dependence of *n* economic variables can be decomposed into *n* univariate distributions and a copula function. The latter fully describes the dependence structure between the variables. Let F and G be the univariate distribution functions of two random variables X and Y. H is assumed to represent the joint distribution function. According to Sklar (1959), there exists a unique copula C that can be expressed as:

$$H(x,y) = C(F(x),G(y)) = C(u,v) \tag{1}$$

Hence, the copula is defined as a multivariate distribution function with uniformly distributed marginals ($u \sim Unif(0,1)$ and $v \sim Unif(0,1)$). The joint density is:

$$h(x,y) = f(x)g(y)c(F(x),G(y)) = f(x)g(y)c(u,v) \tag{2}$$

where c is the copula density, and $f(x)$ and $g(x)$ represent the density functions of variables X and Y, respectively.

Copula functions allow a flexible dependence structure between the *n* random variables and are specially suited when no obvious choice for the multivariate density exists. Copulas are usually more informative than the linear correlation coefficient between random variables, which is not sufficient to describe dependency when the joint distribution in nonelliptical. The Sklar's (1959) theorem allows the researcher to focus on modeling univariate distributions instead of the multivariate one, which usually leads to the construction of better models (Patton, 2006). Copulas relate univariate distributions of any type, i.e., marginal distributions do not have to belong necessarily to the same family. Since the info contained in the marginal distribution is filtered out by means of transforming the original variables into uniform variables, the copula function only contains information on the joint distribution of the *n* variables.

The use of copulas to model joint dependence in the economics literature is very recent and applications have been mainly confined to the financial economics literature (Lai et al., 2009; Hsu et al., 2008; Parra and Koodi, 2006; Patton, 2004, 2006). To the best of our knowledge, this is the first article to use copulas to model price spillovers within the liquid fuel marketing chain. More specifically, and as noted above, we focus on dependence between two pairs of prices: crude oil and biodiesel and crude oil and diesel prices. Our analysis will allow responding the question of whether biodiesel can serve as a tool to reduce the impact on fuel prices of crude oil price fluctuations, and specially of extreme crude oil price increases.

Many previous research papers have identified the presence of asymmetries in vertical price transmission within the fuel markets. We thus use a flexible copula specification that allows for asymmetries in either direction, as well as for symmetric dependence as a special case: the symmetrized Joe-Clayton Copula (Patton, 2006). As an alternative, we also estimate a Gaussian copula, which is the benchmark copula in economics. Different copulas represent different dependence structures and measure the strength of the dependence by means of their parameters (Ning et al., 2008). The bivariate Gaussian copula can be expressed as:

$$C_G(u,v|\rho)=\int_{-\infty}^{\Phi^{-1}(u)}\int_{-\infty}^{\Phi^{-1}(v)}\frac{1}{2\pi\sqrt{(1-\rho^2)}}\exp\left\{\frac{-(r^2-2\rho rs+s^2)}{2(1-\rho^2)}\right\}drds \tag{3}$$

where ρ is a correlation coefficient $-1<\rho<1$ and Φ is the univariate normal distribution function. A shortcoming of the Gaussian copula is that it assumes that the variables u, v are independent in the extreme tails of the distribution. This does not allow capturing the tendency of random economic variables to move together during extreme events. Hence, the Gaussian copula, through its parameter ρ mainly informs of the dependence in the central region of the multivariate distribution.

In contrast, the Joe-Clayton copula measures the probability that the variables are in their lower or upper joint tails and can be defined as:

$$C_{JC}(u,v|\tau^U,\tau^L)=1-\left(1-\left\{\left[1-(1-u)^k\right]^{-\gamma}+\left[1-(1-v)^k\right]^{-\gamma}-1\right\}^{-1/\gamma}\right)^{1/k} \tag{4}$$

where $k=1/\log_2(2-\tau^U)$, $\gamma=-1/\log_2(\tau^L)$, $\tau^U\in(0,1)$ and $\tau^L\in(0,1)$.

Parameters τ^U and τ^L are measures of the tail dependence and are informative of variable dependence during extreme events. In our analysis, tail dependence measures the probability that a relevant increase (decrease) in the diesel or biodiesel price occurs, given the fact that there has been a large increase (decrease) in the crude oil price. Measures of tail dependence are defined as:

$$\lim_{\varepsilon \to 0} \Pr\left[U \le \varepsilon \middle| V \le \varepsilon\right] = \lim_{\varepsilon \to 0} \Pr\left[V \le \varepsilon \middle| U \le \varepsilon\right] = \lim_{\varepsilon \to 0} C(\varepsilon, \varepsilon) / \varepsilon = \tau^L \tag{5}$$

$$\lim_{\delta \to 1} \Pr\left[U > \delta \middle| V > \delta\right] = \lim_{\delta \to 1} \Pr\left[V > \delta \middle| U > \delta\right] = \lim_{\delta \to 1} (1 - 2\delta + C(\delta, \delta)) / (1 - \delta) = \tau^U \tag{6}$$

By construction, the Joe-Clayton copula functional form involves that dependence is always asymmetric, even if $\tau^L = \tau^U$. To overcome this limitation and allow for exact symmetry as a special case, the Symmetrized Joe-Clayton (SJC) copula has been proposed (Patton, 2006), which is symmetric when $\tau^L = \tau^U$.[8]

$$C_{SJC}(u,v|\tau^U,\tau^L) = 0.5\left(C_{JC}(u,v|\tau^U,\tau^L) + C_{JC}(1-u,1-v|\tau^U,\tau^L) + u + v - 1\right) \tag{7}$$

Consistent and asymptotically normal copula parameters are derived using a two-stage estimation procedure by which the marginal distribution models are estimated in a first stage and the copula model is estimated in a second stage (Patton, 2006).[9] Let the conditional joint distribution be parametrized as follows: $H_t(\xi) = C_t(F_t(\varphi_x), G_t(\varphi_y); \theta)$, where $\xi = (\varphi_x, \varphi_y, \theta)$ is the vector containing the marginal parameters (φ_x, φ_y) and the copula parameters θ. The joint density is:

$$h_t(x, y; \xi) = f_t(x_t; \phi_x) g_t(y_t; \phi_y) c_t(F_t(x_t; \phi_x), G_t(y_t; \phi_y); \theta) \tag{8}$$

By taking logarithms and summing across observations, we obtain the log likelihood function:

$$\mathscr{L}(x,y;\xi)=\frac{1}{n}\sum_{t=1}^{n} \log f_t(x_t;\phi_x)+\log g_t(y_t;\phi_y)+\log c_t(F_t(x_t;\phi_x),G_t(y_t;\phi_y);\theta) \tag{9}$$

The equation above can be decomposed into the marginal log likelihoods and the copula log likelihood:

$$\mathscr{L}(x,y;\xi)=\mathscr{L}(\phi_x)+\mathscr{L}(\phi_y)+\mathscr{L}(\phi_x,\phi_y,\theta) \tag{10}$$

In the two-step estimation procedure, the marginal parameters are estimated by independently maximizing the marginal log likelihoods. Conditional upon parameter estimates obtained in the first step, copula parameters are derived optimizing the copula log likelihood. The parameter estimation process can be represented as follows:[10]

$$\hat{\phi}_x=\arg\max_{\phi_x}\frac{1}{n}\sum_{t=1}^{n} \log f_t(x_t;\phi_x) \tag{10}$$

$$\hat{\phi}_y=\arg\max_{\phi_y}\frac{1}{n}\sum_{t=1}^{n} \log g_t(y_t;\phi_y) \tag{11}$$

$$\hat{\theta}=\arg\max_{\theta}\frac{1}{n}\sum_{t=1}^{n} c_t(F_t(x_t;\phi_x),G_t(y_t;\phi_y);\theta) \tag{12}$$

Since none of the two copulas considered, i.e., the Gaussian and the SJC, is nested in the other, we use Rivers and Vuong's (2002) nonnested likelihood ratio test to compare the two competing alternatives.

The models for the marginal distributions of crude oil, diesel and biodiesel prices are described below. These models aim at filtering the information contained in the univariate distributions. Let's denote the logarithm of the crude oil, diesel and biodiesel prices as P_c, P_d and P_b respectively. The two pairs of prices studied are: $(x, y) = (P_c, P_d)$ and $(x, y) = (P_c, P_b)$.

Univariate models for the (P_c, P_b) *price pair analysis:*

$$\Delta P_{c,t} = \alpha_c + \lambda_c v_{cb,t-1} + \sum_{i=1}^{2} \alpha_{c1i} \Delta P_{c,t-i} + \sum_{i=1}^{2} \alpha_{c2i} \Delta P_{b,t-i} + \varepsilon_{c,t} \tag{6}$$

$$\sigma_{c,t}^2 = \omega_c + \omega_{c1} \varepsilon_{c,t-1}^2 + \omega_{c2} \sigma_{c,t-1}^2 \tag{7}$$

$$\Delta P_{b,t} = \alpha_b + \lambda_b v_{cb,t-1} + \sum_{i=1}^{2} \alpha_{b1i} \Delta P_{c,t-i} + \sum_{i=1}^{2} \alpha_{b2i} \Delta P_{b,t-i} + \varepsilon_{b,t} \tag{8}$$

$$\sigma_{b,t}^2 = \omega_b + \omega_{b1} \varepsilon_{b,t-1}^2 + \omega_{b2} \sigma_{b,t-1}^2 \tag{9}$$

Where Δ is the first difference operator, v_{cb} is the error correction term derived from the cointegration relationship between P_c and P_b, and $\varepsilon_{c,t}$ and $\varepsilon_{b,t}$ are normally distributed error terms.[11] Since the copula theory applies to stationary time-series and, as it will be shown in the results section, our price data have unit roots, we take first differenced price series in order to ensure stationarity. Expressions (6) to (9) above involve the assumption that individual energy prices can be fully characterized by a univariate error correction model (ECM) for the conditional mean and a GARCH(1,1) specification for the conditional variance. A normal log-likelihood is used for the estimation of the conditional mean and variance equations.[12] It is widely known that, under the wrong normality assumption, GARCH estimates still yield consistent parameter estimates (Bollerslev and Wooldridge, 1992). Conversely, if other distributions are incorrectly assumed, parameter estimates are inconsistent.

Univariate models for the (P_c, P_d) price pair analysis:

$$\Delta P_{c,t} = \alpha_c + \lambda_c v_{cd,t-1} + \sum_{i=1}^{2} \alpha_{c1i} \Delta P_{c,t-i} + \sum_{i=1}^{2} \alpha_{c2i} \Delta P_{d,t-i} + \varepsilon_{c,t} \tag{10}$$

$$\sigma_{c,t}^2 = \omega_c + \omega_{c1} \varepsilon_{c,t-1}^2 + \omega_{c2} \sigma_{c,t-1}^2 \tag{11}$$

$$\Delta P_{d,t} = \alpha_d + \lambda_d v_{cd,t-1} + \sum_{i=1}^{2} \alpha_{d1i} \Delta P_{c,t-i} + \sum_{i=1}^{2} \alpha_{d2i} \Delta P_{d,t-i} + \varepsilon_{d,t} \tag{12}$$

$$\sigma_{d,t}^2 = \omega_d + \omega_{d1} \varepsilon_{d,t-1}^2 + \omega_{d2} \sigma_{d,t-1}^2 \tag{13}$$

Where v_{cd} is the error correction term derived from the cointegration relationship between P_c and P_d, and $\varepsilon_{c,t}$ and $\varepsilon_{d,t}$ are normally distributed error terms.

After estimation of the univariate ECM-GARCH models, we derive the standardized iid residuals and transform them into uniform $(0,1)$ variables using the non-parametric empirical cumulative distribution function (CDF). Using the nonparametric empirical CDF method is specially useful when the actual distribution of the data is unknown. Conducting goodness-of-fit tests on the marginal models is essential for copula model estimation. Independence of the first four moments of U_t and V_t is assessed by regressing $(u_t - \bar{u})^k$ and $(v_t - \bar{v})^k$

on 10 lags of each variable, for k=1,2,3,4, and using the LM tests proposed by Patton (see Patton, 2006 for further details).

5. Empirical analysis

Our empirical analysis is based on weekly prices for crude oil, diesel and biodiesel, observed from November 5, 2006 to October 5, 2010, which yields a total of 205 observations. Data on diesel and biodiesel[13] prices at the pump, expressed in euros per liter, were obtained from the Spanish Ministry of Industry, Tourism and Trade (2010). International crude oil prices (in US dollars per barrel) were derived from the US Energy Information (2010) dataset. The latter were converted into euros per liter using the European Central Bank (ECB, 2010) exchange rates. Logarithmic transformations of the price series are used in the empirical analysis.

Since price series usually present unit roots, standard unit root testing was carried out and results suggested that prices are non-stationary.[14] As noted above, since the theory of copulas applies to static time-series, we take the logged prices in first differences for the remainder of the analysis. Table 1 presents summary statistics of the first-differenced time series. These statistics show that, during the period of analysis, none of the series had a statistically significant trend. All three series exhibit rather large standard deviations relative to their means, which yields relatively large coefficients of variation (around 16-17 for diesel and biodiesel and around 28.5 for crude oil, which is compatible with Borenstein et al. (1997) who find gasoline prices to be less volatile than crude oil prices.). Compatible with Hammoudeh et al. (2003), we find the series to have positive skewness, though the null hypothesis of no skewness cannot be rejected. We also find that the thickness of the distribution tails is significantly higher than the normal distribution tails, i.e., the series are leptokurtic.

Table 1

Summary statistic for first differenced logged price series.

	Crude oil	Biodiesel	Diesel
Mean	1.575e-3	0.781e-3	0.910e-3
Standard Deviation	0.045	0.013	0.015
T-statistic	0.501	0.844	0.863
Skewness	0.0311	0.045	0.195
Kurtosis (excess)	4.251**	2.047**	2.120**
Jarque-Bera statistic	153.673**	35.699**	39.502**
ARCH LM statistic	42.369**	50.506**	53.697**
Number of observations		204	

Note: ** indicate rejection of the null hypothesis at the 5% significance level. The skewness and kurtosis and their significance tests are from Kendall and Stuart (1958). The Jarque-Bera is the well known test for normality. The ARCH LM statistic is the Engle (1982) test for ARCH effects conducted using 2 lags.

Previous to ECM-GARCH univariate model estimation, the Johansen's (1988) method is applied to test for the existence of an equilibrium relationship between the pairs of prices considered and to derive the error correction terms (v_{cd} and v_{cb}). Compatible with previous research results (see Asche et al., 2003 for example), our findings suggest that crude oil maintains a long-run relationship with diesel and biodiesel prices (see table 2). As it will be shown below when presenting the ECM-GARCH results, while crude oil prices are exogenous for long-run parameters, diesel and biodiesel prices are endogenous. This involves that, while crude oil prices do not react to deviations from the long-run equilibrium relationship, diesel and biodiesel prices respond to reequilibrate the market. Hence, the first (second) cointegration relationship presented in table 2 represents the parity that biodiesel (diesel) prices in Spain need to maintain with international crude oil prices for the biodiesel (diesel) industry to be in equilibrium. As expected, the parameters representing long-run price links suggest that an increase in crude oil prices will cause an increase in diesel and biodiesel prices as well. This is not surprising since diesel is obtained by refining crude oil and biodiesel is not commercialized in pure form, but blended with petroleum diesel.

Table 2

Johansen λ_{trace} test for cointegration and cointegration relationships.

Crude oil – Biodiesel price pair (P_c, P_b)				Crude oil – Diesel price pair (P_c, P_d)			
Ho	Ha	λ_{trace}	P-value	Ho	Ha	λ_{trace}	P-value
$r=0$	$r>0$	29.412	0.003	$r=0$	$r>0$	30.504	0.002
$r\leq 1$	$r>1$	6.522	0.168	$r\leq 1$	$r>1$	6.835	0.152
Cointegration relationship (standard errors in parenthesis) (P_c, P_b)				Cointegration relationship (standard errors in parenthesis) (P_c, P_d)			
$P_{b,t} - 0.557^{**} P_{c,t} - 0.624^{**} = v_{cb,t}$ (-16.649) (-16.430)				$P_{d,t} - 0.589^{**} P_{c,t} - 0.656^{**} = v_{cd,t}$ (-16.267) (-15.973)			

Note: r is the cointegration rank. ** denotes statistical significance at the 5% level.

Results derived from ECM-GARCH model estimation are presented in tables 3 and 4 for the (P_c, P_b) and (P_c, P_d) price pairs, respectively. In the next lines we focus on the results derived from the (P_c, P_b) pair. The conditional mean equation for the biodiesel price shows that current price levels are influenced by past realizations of the biodiesel and crude oil prices and by the deviations from the long run biodiesel-crude oil price parity (table 3). The conditional variance equation suggests that past biodiesel market shocks contribute to increased current biodiesel price volatility. GARCH model parameter estimates are all positive, which guarantees that both in-sample and out-sample variance estimates are positive. Further, since $\omega_{b1} + \omega_{b2} < 1$, the GARCH process is stationary and the unconditional long-run variance $\sigma_b^2 = \omega_b / (1 - \omega_{b1} - \omega_{b2})$ is equal to 6.2e-5.

In contrast with biodiesel, crude oil price is only influenced by its own past realizations, not responding to long-run disequilibriums (table 3). The conditional variance equation provides evidence that both past market shocks and volatility involve an increase in current crude oil price volatility. GARCH parameter estimates are all positive and yield a stationary volatility process with an unconditional variance $\sigma_c^2 = 1.7\text{e-}3$. Volatility in crude oil prices is thus higher than volatility in biodiesel prices, which is compatible with Vedenov et al. (2006) results for the US ethanol market.

Table 3

Results for the marginal distributions. Crude oil – Biodiesel price pair (P_c, P_b).

	Biodiesel, $j=b$	Crude oil, $j=c$
$\Delta P_{b,t-1}$	0.264**	0.013
	(0.081)	(0.301)
$\Delta P_{b,t-2}$	-0.051	-0.021
	(0.053)	(0.249)
$\Delta P_{c,t-1}$	0.160**	0.206**
	(0.012)	(0.087)
$\Delta P_{c,t-2}$	0.025	-0.120*
	(0.018)	(0.070)
$v_{cb,t-1}$	-0.038**	-0.003
	(0.010)	(0.056)
ω_j	2.278e-5**	5.769e-5
	(9.140e-6)	(3.765e-5)
ω_{j1}	0.385**	0.134**
	(0.135)	(0.044)
ω_{j2}	0.248	0.832**
	(0.167)	(0.049)
Ljung-Box Q(10) statistic	6.060	11.148

Note: *(**) denotes statistical significance at the 10% (5%) level.

We now focus on discussing the results for the (P_c, P_d) price pair (table 4). The ECM-GARCH for the diesel price shows how current price levels respond to past crude oil prices and to market disequilibriums. The diesel price volatility grows with past market shocks, but not with past volatility. While ω_{d2} is negative, it is not statistically significant. The unconditional long-run variance for diesel prices is $\sigma_d^2 = 1.1\text{e-}4$, being thus higher tan biodiesel price volatility.

Compatible with the (P_c, P_b) price pair results, the crude oil price model for the pair (P_c, P_d) confirms that crude oil prices only depend on their lagged levels, while crude oil price volatility depends on past market shocks and volatility, being the long-run volatility on the order of 1.7e-3.

Table 4

Results for the marginal distributions. Crude oil – Diesel price pair (P_c, P_d).

	Diesel, $j = d$	Crude oil, $j = c$
$\Delta P_{d,t-1}$	-0.056	0.101
	(0.086)	(0.201)
$\Delta P_{d,t-2}$		0.185
		(0.184)
$\Delta P_{c,t-1}$	0.182**	0.223**
	(0.020)	(0.085)
$\Delta P_{c,t-2}$	0.075**	-0.148
	(0.022)	(0.094)
$v_{cd,t-1}$	-0.052**	0.048
	(0.012)	(0.072)
ω_j	1.088e-4**	5.934e-5*
	(2.396e-5)	(3.157e-5)
ω_{j1}	0.244**	0.135**
	(0.124)	(0.042)
ω_{j2}	-0.272	0.830**
	(0.166)	(0.045)
Ljung-Box Q(10) statistic	15.396	10.406

Note: *(**) denotes statistical significance at the 10% (5%) level.

The Ljung-Box test applied to the univariate models does not allow rejecting the null of no autocorrelated residuals from lag 1 to 10 at the 5% level, which is an indicator that models are well specified. The LM tests proposed by Patton (2006) and applied to test independence of the first four moments of U_t and V_t are presented in table 5. The null that the marginal models are well specified cannot be rejected at the 5% level.[15]

Table 5

Tests of the transformed variables.

	Crude oil – Biodiesel price pair (P_c, P_b)	
	P_b	P_c
First moment LM test	0.732	0.628
Second moment LM test	0.999	0.073
Third moment LM test	0.597	0.953
Fourth moment LM test	0.999	0.429
	Crude oil – Diesel price pair (P_c, P_d)	
	P_d	P_c
First moment LM test	0.724	0.091
Second moment LM test	0.999	0.819
Third moment LM test	0.638	0.767
Fourth moment LM test	0.999	0.998

Note: P-values from the LM tests of serial independence (Patton, 2006) of the first four moments of U_t and V_t are presented in the table.

Table 6 presents the results for the Gaussian and SJC copulas. The correlation coefficient derived from the Gaussian copula is statistically significant and slightly above 0.4 for both pairs of prices, indicating that in the central region of the distribution, an increase in the international crude oil price entails an increase in diesel and biodiesel price levels. Since the Gaussian copula assumes zero tail dependence, dependency during extreme market events is studied with the SJC copula.

The lower tail dependence for the (P_c, P_b) price pair is equal to 0.3 and is statistically significant. Conversely, the upper tail dependence is much smaller (0.1) and is not statistically different from zero. This implies that price declines are more prone to occur together than price increases. In other words, biodiesel and crude oil prices are more dependent during extreme market downturns. This involves that while extreme declines in crude oil prices will be passed on to biodiesel prices, extreme increases will not be transferred. This asymmetric price dependence is compatible with results derived by Borenstein et al. (1997) or Galeotti et al. (2003) and is an indicator that blending biodiesel with diesel can serve as a means to control for extreme energy price increases. In this regard, it would be useful to homogenize blending practices across different countries so as to facilitate refining, transportation, delivery and trade of biofuels, which in turn would ensure global biofuel availability, its associated benefits and would contribute to reduce biofuel production costs (US Government Accountability Office GAO, 2007).

Upper and lower tail dependency measures for the (P_c, P_d) price pair are both statistically significant and virtually equal. Hence, the dependence between prices is equally relevant during extreme downturns than during extreme upturns of the two markets. Thus, while biodiesel protects consumers against crude oil price increases, diesel does not. The Rivers and Vuong (2002) nonnested likelihood ratio test does not allow distinguishing between the Gaussian and SJC models, which involves that both models provide useful information to characterize price behavior.

Table 6

Results for the copula models

	Crude oil – Biodiesel price pair (P_c, P_b)	Crude oil – Diesel price pair (P_c, P_d)
	Gaussian copula	
ρ	0.418**	0.435**
	(0.064)	(0.064)
Copula likelihood	19.409	21.189
	SJC copula	
τ^U	0.112	0.254**
	(0.114)	(0.117)
τ^L	0.312**	0.244**
	(0.079)	(0.097)
Copula likelihood	18.015	19.659

Note: *(**) denotes statistical significance at the 10% (5%) level.

6. Concluding remarks

While biofuel policies can target a wide array of objectives, from socio-economic to environmental, our article studies the capacity of biofuels (biodiesel) to reduce the vulnerability of national economies to energy price fluctuations. This is specially relevant in light of the high dependence of the EU's transportation sector on crude oil imports, that makes this region specially vulnerable to crude oil price spikes.

Since biodiesel is produced from renewable energy sources such as agricultural commodities, its price should be less subject to crude oil price fluctuations. Further, the usual practice of commercializing biodiesel blended with diesel so that it can be used in existing motor vehicles, should not only ensure a large-scale biofuel penetration in the motor fuel market, but should also contribute to protect consumers against important increases in crude oil prices.

Our article studies the link between two pairs of prices: crude oil and biodiesel blends, and crude oil and diesel prices in Spain. We are particularly interested in modeling this dependence during extreme market events, which are the most likely to have relevant economic impacts. Copula models are used to assess dependence between the pairs of prices considered. These models are specially suited when no obvious choice for the multivariate density characterizing price dependence exists. Copulas allow the researcher to focus on modeling univariate distributions instead of the multivariate one, which usually leads to the construction of better models.

Research results suggest an asymmetric dependence between the crude oil and the biodiesel price, which protects consumers against extreme crude oil price increases. Diesel and crude oil prices, in contrast, show a symmetric dependence by which both extreme crude oil price increases and decreases are equally likely to be passed on to consumers. Hence, our analysis suggests that promoting biofuels can be a useful tool to reduce national economies' vulnerability to crude oil price increases.

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Footnotes

[1] Biofuels are estimated to be able to create 16 jobs per thousand tons of oil equivalent (toe) (Biofuels Research Advisory Council, 2006).

[2] These consist of mandatory uptakes that set a minimum biofuel share that suppliers have to comply with.

[3] Repealed by Directive 2009/28/EC.

[4] The predominance of biodiesel in the EU contrasts with bioethanol being the most relevant biofuel in the world. In 2006, for example, global consumption of biodiesel was 5.3 million toe, while global bio-ethanol consumption was on the order of 20 million toe (Pelkmans et al., 2008).

[5] Around 65% of EU's rapeseed oil production was devoted to produce biodiesel in 2008 (Pelkmans, 2009).

[6] See Grasso and Manera (2007) for an exhaustive literature review on the price transmission along the gasoline marketing chain.

[7] A second line of research that we do not review here has been based upon structural models.

[8] Joint dependence may be time-varying. To allow for this behavior Patton (2006) has proposed the concept of conditional (time-varying) copula. Time-varying dependence is modeled by assuming that the parameters of the copula evolve according to some pre-specified equation. While we considered time-varying copula parameters, model selection criteria (Parra and Koodi, 2006) recommended the use of the constant parameter specifications.

[9] Single stage estimation usually makes numerical optimization of the log-likelihood function difficult.

[10] The variance-covariance matrix of copula parameters is obtained using the Godambe information matrix.

[11] The number of lags used in marginal models was determined based on statistical significance and parsimony.

[12] While the Student's t log-likelihood was also considered, convergence of the estimation algorithm was not always possible and when it was, the extreme large value of the degrees of freedom parameter suggested that the normal density was a better representation of the univariate price behavior.

[13] The latter corresponding to average prices of biodiesel blends.

[14] Details from unit root testing are available from the authors upon request. Previous literature has shown that when price series have a unit root, shocks to the series in levels have permanent effects, while shocks to first-differenced price series are only transitory. This tends to cause volatility clustering and non-constant conditional price variance that involves that shocks to the price series affect their volatility for several forthcoming periods (Ewing et al., 2002).

[15] The Kolmogorov-Smirnov test confirms that the transformed series are Uniform(0,1).