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Corn Market Uncertainty and US Ethanol Prices

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Does Corn Market Uncertainty Impact the US Ethanol Prices?

Abstract

The growing interest in biofuel as a green energy source has intensified the linkages between corn and ethanol markets, especially in the United States that represents the largest producing and exporting country for ethanol in the world. In this study, we examine the effect of corn market uncertainty on the price changes of US ethanol applying a set of GARCH-jump models. We find that the US ethanol price changes react positively to the corn market volatility shocks after controlling for the effect of oil price uncertainty. In addition, we document that the impact of corn price volatility on the US ethanol prices appears to be asymmetric. Specifically, only the positive corn market volatility shocks are found to influence the ethanol market returns. Our findings also suggest that time-varying jumps do exist in the ethanol market.

Keywords: Corn price uncertainty; US ethanol market; Oil price volatility; GARCH–jump model; Asymmetry; Volatility shocks.

Introduction

The production of biofuel, especially corn-based ethanol, has grown significantly in the past 12 years following the adoption of US energy security-related policies such as the Renewable Fuel Standard, a part of the Energy Policy Act of 2005. According to Chakravorty et al. (2017), about 40% of US corn is currently used to produce biofuels. In this context, Natanelov et al. (2013) argue that energy security-related policies such as corn-for-ethanol have magnified the link between the markets of corn and ethanol. In addition to the contributing role of biofuel policies regarding energy independence and decarbonization in the biofuel expansion, there are other studies indicating that the rising crude oil prices have also created an incentive to use alternative energy sources such as corn-based ethanol (Serra et al., 2011a; Papiez, 2014).

Vedenov et al. (2006) add that highly volatile crude oil prices reduce crude oil competitiveness and represent a further incentive to adopt alternative energy sources. Chiu et al. (2016) also document that biofuels have been brought into the energy market as a substitute in order to moderate the amount of carbon emissions released into the atmosphere as well as to prevent energy prices from rising. Recently, Smith and Porter (2018) highlight the importance of biofuels or bioenergy research in the Intergovernmental Panel on Climate Change (IPCC) Assessments based on the articles published between 1990 and 2017.

However, it is noteworthy that the recent growth in ethanol production seems to cause a significant fall in global oil prices (Lipsky, 2008; Chiu et al., 2016). For example, the National Renewable Energy Laboratory (2008) reports that a mixture of 90% gasoline and 10% ethanol would have depressed the prices of gasoline by between $0.19 and $0.50 per gallon. Additionally, a scholarly work by Du et al. (2011) reveals that the bioethanol production has reduced gasoline prices by an average of $0.29 per gallon from 2000 to 2011 in the US, whilst the Midwest area of the country appears to be the most highly affected region. The study further shows that a major reduction in gasoline prices is achieved in terms of the highest amount of ethanol production. Moreover, a study by the Renewable Fuels Association (2013) contends that the crude oil prices would be approximately $15-$40 a barrel higher in the absence of bioethanol production additives. The reason behind such facts is that the price impact of bioethanol use can be observed as a positive shock to the gasoline supply (Marzoughi and Kennedy, 2012).

In the United States ethanol is used as a component of gasoline, and produced mainly from corn. Thus the market prices for ethanol, corn and fuels can be correlated with each other because of the ethanol mandate which connects those markets. Accordingly, a growing body of empirical studies sheds light on the links between crude oil, ethanol and corn prices. Zhang et al. (2010), for instance, use monthly price data for corn, rice, soybeans, sugar, and wheat as well as ethanol, gasoline, and oil from 1981 to 2007 to investigate linear cointegration. The authors report that both corn and gasoline prices impact ethanol prices, and that since oil prices influence gasoline prices, the crude oil prices affect ethanol prices as well. Moreover, Kristoufek et al. (2012) study the correlations between a wide array of food and fuel commodity prices in the United States and European Union (EU) over the period 2003 to 2008. The authors find significant dynamic linkages between food and fuel prices with biofuels connecting these markets. When analyzing the volatility spillovers between the US ethanol and corn prices, Trujillo-Barrera et al. (2012) observed that unidirectional risk is documented between corn and ethanol markets. Furthermore, a study by Papiez (2014) uses a rolling regression approach applied to an augmented-VAR framework proposed by Toda and Yamamoto (1995) to explore the association between crude oil, ethanol and corn prices. The study reports that the price of crude oil influences the prices of both corn and ethanol. More recently, Kristoufek et al. (2016) use the wavelet coherence methodology to investigate the relations between prices in the US ethanol and corn markets. For both of these markets, the authors document that the long-run relationship between prices of ethanol and corn is positive, strong and stable in time. They further add that the prices of feedstock lead the prices of ethanol and not the other way around. To sum up, rising corn prices lead to an increase in ethanol prices, which is not surprising given that corn has emerged as the main feedstock to produce ethanol in the US market. Moreover, an upturn in oil price also causes an increase in ethanol prices due to the fact that energy prices tend to lead the food prices (Serra at al., 2011b). Therefore, the existing literature suggests that the global ethanol prices are affected by both corn and fossil fuel prices, with the association between corn and ethanol prices appearing to have been strengthened following the government mandates requiring and increased use of ethanol as a component in gasoline production.

Based on the outcomes of the existing studies, we can postulate that corn price uncertainty can have an effect on ethanol prices and that the effect might be asymmetric. Furthermore, and given the results in the aforementioned literature, crude oil uncertainty can play a role in the association between the corn price uncertainty and ethanol market price changes. Accordingly, the present study attempts to respond to the following questions: 1) Does the corn price uncertainty, measured by the corn market implied volatility (CIV), have a positive impact on the US ethanol market returns? 2) Does the effect of corn market volatility shocks hold while controlling for the effects of oil price uncertainty? 3) Does the effect of a positive change in corn price volatility on the ethanol market returns differ from that of a negative change? To the best of our knowledge, this is the first study that addresses such timely and crucial research questions within the existing literature on the US corn-ethanol nexus. Importantly, CIV index is used as an indicator of corn market uncertainty. Wang et al. (2012) also argue that the corn VIX will improve the volatility forecasting and enhance market participants' ability to more accurately gauge the price risk in the corn market. Therefore, it is motivating to examine whether the information content of corn price volatility affects the US ethanol market returns.

Methodologically, we employ the GARCH-jump model proposed by Chan and Maheu (2002). In the case of our data set, considering the jump approach could be beneficial, since unlike the traditional GARCH models, it can capture the effects of extreme news or abnormal information arising from abnormal trading, crashes, and similar other shock type events (Fowowe, 2013 and Dutta et al., 2017). Moreover, in addition to accounting for smooth persistent changes in volatility, the model also captures the discrete jumps in the market returns. Our findings reveal that variations in the corn price volatility lead the change in the price of ethanol. In particular, we document a strong positive association between these two markets. This finding is not surprising, since corn is the main feedstock for the US ethanol industry and thus a rise in the corn price uncertainty would account for the upsurge in ethanol price. Moreover, previous studies such as Zhang et al. (2010), Zilberman et al. (2012) and Dutta (2018) argue that the global ethanol prices are affected by both food and crude oil prices. Therefore, we extend our analysis by investigating the link between corn and ethanol markets after controlling for the effect of OVX. The results show that the effect of CIV is still statistically significant at 5% level. We further document that the impact of corn volatility is asymmetric indicating that the rise and fall in CIV do not have similar effects on the returns of the US ethanol market. The findings also confirm the existence of time-varying jumps in ethanol returns.

Our study extends the prior literature in several aspects. First, this is the initial study to examine the links among corn, ethanol and crude oil markets using the corn and oil market implied volatility indices. That is, we attempt to model the realized volatility of the US ethanol market, considering the global anticipation of future corn and oil market uncertainties, measured by their respective implied volatility indices. Several researchers argue that employing implied volatility data is advantageous for several reasons. As indicated by Dutta et al. (2017), the implied volatility index is derived from option prices, which make it a good indicator of market uncertainty (in our case, the uncertainty of corn and crude oil markets). Implied volatilities not only contain historical volatility information, but also investors' expectations of future market conditions (Bouri et al., 2017; Ji et al., 2018). Second, previous studies argue that in addition to food price shocks, volatile oil prices also influence the changes in global ethanol prices. While the existing literature investigates the oil-corn-ethanol nexus using traditional oil market (spot and/or futures) prices, our study considers the information content of oil volatility index instead of crude oil price series arguing that OVX could reveal more information than do the conventional price indices.

Besides, since OVX, being a forward-looking measure, represents the markets' consensus on the expected future uncertainty, using such implied volatilities could also improve the forecasts of ethanol price volatility. Third, we contribute to the scarce literature on the uncertainty transmission mechanism among crude oil, ethanol and corn prices in the United States. Understanding such spillover effects across time and markets is important, since volatility is related to the rate of information flow to the markets. Earlier studies have also shed light on the importance of assessing the uncertainty transmission relationships across energy and agricultural markets. For example, Gardebroek and Hernandez (2013) stressed on the conditional volatility spillover to investigate the directionality and dependence among oil, corn and ethanol markets. Additionally, Nazlioglu et al. (2013) also contend that the energy and agricultural markets have recently been characterized by more volatile dynamics that call for deeper analyses of volatility transmission between these markets. It is thus essential for investors and policymakers to gain deeper understanding about the role of corn and oil market uncertainty in the jump dynamics of the US ethanol market returns for making better investment and hedging decisions. This paper thus makes a novel extension to earlier studies such as Zhang et al. (2010), Serra et al. (2011 a, b), Trujillo-Barrera et al. (2012), Kristoufek et al. (2012, 2016), among others. Finally, unlike the previous studies, we consider the jump behavior in the US ethanol market returns via GARCH-jump models (Chan and Maheu, 2002) when uncovering any evidence of asymmetric impacts on the ethanol market returns by separating the corn price shocks into positive and negative components.

Materials and methods

Data description

Our data are retrieved from the Thomson Reuters DataStream database. They include the daily US ethanol market prices (only the anhydrous ethanol is used in the USA) and the

Chicago Board of Trade (CBOT) CIV that represents the implied volatility of options that trade on corn futures. In addition, we use the crude oil implied volatility index (OVX), introduced by Chicago Board Options Exchange (CBOE), as an indicator of oil price uncertainty. It is noteworthy that the US ethanol prices are based on the futures contracts. The sample period starts from 2 June, 2011 and ends to 31 August, 2016, based on the availability of CIV data.

Table 1 reports the descriptive statistics for the ethanol return series (calculated as the log change of the price series) and the two implied volatility indices (in levels). It appears that ethanol returns are negatively skewed, implying that large negative returns are more common than large positive returns. The kurtosis is higher than 3 for the ethanol market implying that the return index has a leptokurtic distribution with asymmetric tails. Fig. 1, which displays both ethanol price and return indexes, also indicates the presence of volatility clustering and hence the GARCH process is a preferred option for modeling the return series. Moreover, the graphical presentation of ethanol prices (see Fig. 1a) further shows that large price movements seem to occur in the US biofuel market. It is therefore crucial to use a model that can capture both volatility dynamics and jump behavior of ethanol prices so that the future volatility can be measured more closely.

Regarding the two volatility indices, OVX exhibits more volatility than the CIV. In addition, the Jarque-Bera test demonstrates that none of these indexes is normally distributed. Next, Fig. 2 depicts the two implied volatility indices and shows that the OVX series is less stable than the CIV series. Specifically, several spikes are observed in the implied volatility of the oil market, which is not the case for the corn market. Previous studies (Dutta et al., 2017; Ji et al., 2018) argue that economic and political events lead to hikes in oil market volatility.

GARCH-jump model

We use a simple regression equation to explain the behavior of US ethanol price changes (i.e., returns) in the form of an AR(2)-X model, that is, an autoregressive two-lag model for returns R_t with an added explanatory variable, i.e. the change in the implied corn market volatility index $\Delta CIV_t = CIV_t - CIV_{t-1}$. Hence, the basic regression equation is expressed in the following form.

$$R_t = \pi + \mu_1 R_{t-1} + \mu_2 R_{t-2} + \delta \Delta CIV_t + \epsilon_t,$$

(1)

where π is the constant term in the AR(2) process for the returns, and ϵ_t refers to the error term at time *t*. However, based on the above discussion on the possibilities of shock effects in the market and asymmetries in the return series, we want to examine the possibility for a GARCH-jump process regarding the error term ϵ_t in the above regression equation along the ideas given in Chan and Maheu (2002). Put it simply, their approach implies that the error term process ϵ_t is a sum of two components, which is expressed by equation 2.

$$\epsilon_t = \epsilon_{1t} + \epsilon_{2t}. \tag{2}$$

In other words, the standard conditional volatility defined by GARCH (1,1)-type error part ϵ_{1t} has a representation

$$\epsilon_{1t} = \sqrt{h_t} z_t, \quad z_t \sim NID(0,1)$$

$$h_t = \omega + \alpha \epsilon_{1t-1}^2 + \beta h_{t-1}, \tag{3}$$

which implies that the variance of the first error term component is dependent on its own past values and squared values of the past first error term components. However, more importantly, the second component (ϵ_{2t}) is a jump innovation process which consists of abnormal price movements with $E(\epsilon_{2t}|I_{t-1}) = 0$, where I_{t-1} describes the information set. Now ϵ_{2t} is defined as the discrepancy between the jump component and the expected total jump size $(\theta\lambda_t)$ between t-1 and t, i.e.,

$$\epsilon_{2t} = \sum_{l=1}^{n_t} U_{tl} - \theta\lambda_t, \tag{4}$$

where U_{tl} denotes the jump size, assumed to be normally distributed with mean θ and variance d^2, and $\sum_{l=1}^{n_t} U_{tl}$ is the jump component, whereas n_t defines the number of jumps. It is assumed that n_t is distributed as a Poisson variable with an autoregressive conditional jump intensity (ARJI) expressed by equation 5.

$$\lambda_t = \lambda_0 + \rho\lambda_{t-1} + \gamma\xi_{t-1}, \tag{5}$$

where λ_t is the time-varying conditional jump intensity parameter, and $\lambda_t > 0$, $\lambda_0 > 0$, $\rho > 0$ and $\gamma > 0$. Note that ρ and γ are the parameters of most recent jump intensity (λ_{t-1}) and the intensity residuals (ξ_{t-1}) respectively. The estimation procedure is based on maximum likelihoods estimation, and the log-likelihood function can be expressed as: $L(\Omega) = \sum_{t=1}^{T} \log f(R_t|I_{t-1};\Omega)$, where $\Omega = (\pi, \mu_1, \mu_2, \delta, \omega, \alpha, \beta, \theta, d, \lambda_0, \rho, \gamma)$ denotes the parameter vector for the whole model described in equations (1) – (5). For comparison purposes, we also consider the constant intensity jump model by Jorion (1988), which simply assumes that λ_t does not vary over time, i.e., $\lambda_t = \lambda_0$.

Results

Results of the GARCH-jump model

Results from the estimation of the autoregressive conditional jump intensity model for ethanol market returns are reported in Table 2. The results demonstrate that the GARCH parameters are statistically significant at 1% level, suggesting the existence of strong ARCH and GARCH effects. The sum of α and β also indicates an adequate degree of persistence in the return fluctuations.

Furthermore, the corn market implied volatility (CIV) is found to increase the ethanol market returns as evidenced by its statistically significant positive coefficient (δ). That is, the US ethanol price returns are significantly driven by the information content of CIV. This finding is not surprising since corn is the main feedstock for the US ethanol industry. Prior studies report similar findings (Kristoufek et al., 2016; Serra et al., 2011 a, b). Additionally, Gardebroek and Hernandez (2013) document that major events that disturb the US corn production, such as the 2012 drought, would induce further uncertainty in the US ethanol industry. Chiu et al. (2016) also indicate that corn prices represent an important factor driving the changes in ethanol prices in the U.S. Our above-mentioned results have implications for policymakers and point to the existence of a strong link from an agricultural commodity, in our case corn, to the US biofuel markets.

The empirical results in Table 2 also suggest that the jump parameters are commonly significant, implying that jumps do exist in the ethanol return series and they vary over time. The negative coefficient of the jump in the mean indicates that the jump behavior driven by abnormal information has a negative impact on returns, while the positive coefficient of the jump in the variance process implies that volatility driven by abnormal information has a positive effect on the overall volatility of returns (see also Fowowe, 2013). The findings further reveal that all the jump intensity parameters (λ_0, ρ, γ) are also statistically significant, suggesting that the jump intensity varies over time (as e.g. in Dutta et al., 2017). Additionally, these parameters satisfy the constraints $\lambda_0 > 0$, $\rho > 0$ and $\gamma > 0$ and hence, we can infer that the GARCH-jump model is correctly specified for describing the jump behavior in the ethanol market returns. Furthermore, the positive values of ρ and γ indicate that the current jump intensity (λ_t) is affected by the most recent jump intensity (λ_{t-1}) and the intensity residuals (ξ_{t-1}). We also report that the high values of ρ and γ suggest a high degree of persistence in the jump intensity.

Measuring the joint effects of corn and crude oil market volatilities

Next we investigate the connection between the corn price uncertainty and the ethanol market returns, when controlling for the effect of oil volatility shocks measured by the oil market volatility index (OVX). To do so, we extend the regression model in Equation (1) as follows:

$$R_t = \pi + \mu_1 R_{t-1} + \mu_2 R_{t-2} + \delta \Delta CIV_t + \psi \Delta OVX_t + \epsilon_t \quad (6)$$

In model (6), a statistically significant value for the parameter ψ implies the presence of a direct link between the global oil market uncertainty and the US ethanol market returns. The results reported in Table 3 suggest that, although OVX operates as a moderator in the GARCH-jump model, the impact of CIV index is still statistically significant at 5% level. It is further noteworthy that the OVX is a major determinant of the ethanol market price movements, as the corresponding coefficient is highly significant at 1% level. These findings partially support the results of Serra et al. (2011b), which show that in a situation where the ethanol markets are affected by turbulence, changes in oil prices will cause notable volatility in ethanol prices, too. Moreover, in a similar research, Serra et al. (2011a) find that the increased volatility in crude oil markets results in increased volatility in ethanol markets. In addition, Gardebroek and Hernandez (2013) report that the recent increased demand of ethanol, due to rising oil prices, may trigger further demand for corn, leading to additional price volatility in corn prices. Given the fact that the US ethanol industry is mainly corn-based, an increase in oil price ultimately affects the ethanol market. Chiu et al. (2016) also find that the crude oil price has an influence on the price of ethanol as bioethanol is considered to be an alternative fuel used to overcome the pressures to higher oil prices.

Testing for asymmetric impacts of the corn market volatility

Until now, we have documented that the CIV index has significant influences over the US ethanol market returns. It would be interesting to examine whether such impacts are asymmetric. This experiment will allow us to determine whether positive corn market volatility (i.e., positive changes in the volatility index) affects ethanol returns more than the negative corn volatility (i.e., negative changes in the volatility index). An economic implication or reasoning for investigating the asymmetric impact of corn price uncertainty on ethanol market is that if the high corn volatility regime (i.e. when the volatility is higher than the average), compared to the low volatility case (i.e. when the volatility is lower than the average), has stronger (positive) effects on ethanol prices, then, for instance, the weather conditions that affect the corn production and hence the volatility of the corn market prices will certainly have a substantial effect on the ethanol prices. Such situation leads to a need for asymmetric analysis of the association between corn and ethanol markets.

For this purpose, we make an extension to our original mean model for the ethanol returns, specified in Equation (1), based on

$$R_t = \pi + \mu_1 R_{t-1} + \mu_2 R_{t-2} + \varphi_1 \Delta CIV_t^+ + \varphi_2 \Delta CIV_t^- + \epsilon_t.$$

(7)

In the above model, $\Delta CIV_t^+ = \max(\Delta CIV_t, 0)$ indicates a positive corn market volatility shock and $\Delta CIV_t^- = \min(\Delta CIV_t, 0)$ refers to a negative corn market volatility shock, where again, $\Delta CIV_t = CIV_t - CIV_{t-1}$. We then test for the null hypothesis $H_0: \varphi_1 = \varphi_2$ to assess if asymmetric impacts exist between the two markets.

The estimation results of model (7), displayed in Table 4, are in line with the results previously reported in Table 2. That is, the US ethanol market returns are highly sensitive to the corn market volatility shocks. Specifically, only the positive corn market volatility shocks are found to influence the ethanol market returns. Our findings further indicate the presence of strong ARCH and GARCH effects in the ethanol market returns. In addition, the jump intensity parameters $(\lambda_0, \rho, \gamma)$ are all statistically significant confirming the existence of time-varying jumps in the ethanol market returns. Hence, both the linear and non-linear specifications of the corn market volatility shocks suggest a significant impact of corn market uncertainty on the US ethanol returns.

Furthermore, for comparing the statistical significance of the coefficients φ_1 and φ_2, we performed a likelihood ratio (LR) test, where the null hypothesis is $H_0 : \varphi_1 = \varphi_2$. For the LR-test we obtain the values of the maximum likelihood function from the constrained model $(L(\widetilde{\Omega}))$, and alternatively, from the unconstrained model $(L(\widehat{\Omega}))$. Then the LR statistic $(= 2\frac{L(\widetilde{\Omega})}{L(\widehat{\Omega})})$ follows the chi-squared distribution assuming that the null hypothesis is true. According to our results, the null hypothesis can be rejected because the LR test is significant at 5% level, so the impacts of the corn market volatility shocks on the ethanol market returns appear to be asymmetric. That is, the rise and fall in CIV changes would seem to have uneven effects on the returns of the US ethanol market.

Moreover, we perform a similar analysis to examine the asymmetric impact of crude oil volatility and the results are presented in Table 5. These findings suggest that like the CIV index, OVX also has an asymmetric impact on the US ethanol price changes. In addition, the jump parameters are also found to be highly significant confirming our previous outcomes.

The presence of this asymmetric linkage between the markets under study could have important implications for researchers and policymakers. Researchers, for instance, might consider applying appropriate models that take such non-linear relationships into account. Policymakers, on the other hand, could use these findings to guide the biotech companies to be more aware of the adverse movement of corn price and its consequences. To sum up, the asymmetric effects of corn volatility shocks should receive a special attention when modeling the volatility of ethanol prices.

Robustness Test

This section reports the results from a robustness test by using the CIV return series instead of the CIV levels series. We compute the logarithmic returns for the CIV as follows: $RC_t = (\ln CIV_t - \ln CIV_{t-1}) \times 100$ and then rerun our main model. Table 6 presents the results of our robustness test using the CIV return series. These findings also mirror those exhibited in Table 2. That is, we report that increases in the ethanol market returns are followed by increases in the corn market returns. In other words, the ethanol prices respond positively to the changes occurring in the corn volatility index. In addition, the significant jump coefficients imply that jumps do exist in the fuel returns and that jump intensity tends to be varying over time. We thus conclude that our findings are quite robust to the use of CIV return series.

Moreover, we conduct an additional test to check the robustness of our findings by performing subsample analyses. Our first subsample covers the period from 2011 to 2013, while the second one ranges from 2014 to 2016. During the second subsample period, the oil industry experiences a downturn which introduces a number of hikes in OVX (see Fig. 2). Oversupply of crude oil, declining demand and the Iran nuclear deal are some of the probable issues causing such economic stress in global oil market. Our findings, exhibited in table 7, are consistent with those reported in Table 2. We thus conclude that the results of our empirical investigation are robust as they are not sensitive to changes in the sample period.

Discussion

Our main empirical findings document that the US ethanol market returns are strongly linked to the corn market price volatility. More remarkably, while combining the CIV with OVX to detect their joint effects on the ethanol markets, we report that the US ethanol market is substantially affected by the volatilities of both corn and crude oil markets. Further analysis reveals that the effect of CIV on the US ethanol futures prices appears to be asymmetric. We thus show that the positive corn market volatility shocks have more significant influences over the ethanol market returns than the negative corn market volatility shocks have. These results suggest a number of implications for policymakers.

First, governments should take effective measures to help stabilize the corn markets. One possible strategy could be to increase the levels of ethanol feedstock reserves which, in turn, results in lower food grain prices. Moreover, proper steps should also be taken to minimize the impact of oil market shocks on corn prices. For example, governments could benefit from building their strategic petroleum reserves, as the oil reserve is essential for the countries that are highly dependent on imported oil (Zhang and Tu, 2016). Another possibility is that governments can tax the fossil fuel usage. Taking such steps will promote the use of renewable fuels and hence the global dependency on crude oil could be efficiently reduced. Overall, it is important for policy makers and market investors to react effectively to global oil price shocks and moderate the price volatility of agricultural commodities (Zhang and Qu, 2015).

Second, due to a strong positive connection between feedstock and first generation biofuels, the cost of ethanol production heavily depends on the feedstock prices which, in turn, have risen as a consequence of the worldwide increasing demand for ethanol fuel. It is therefore essential to develop second generation biofuels. Natanelov et al. (2013), for instance, contend that biofuels derived from cellulosic plant material could provide a possible means to tackle the limitations of first generation biofuels. Gardebroek and Hernandez (2013) also suggest that a shift towards second-generation biofuels, if technically and economically feasible, could help, in turn, to reduce the price volatility in ethanol markets.

Last but not least, the existence of asymmetric association between the corn and biofuel markets sould shift the investigators from applying linear models to the application of non-linear approaches in the analysis of market dependencies. Besides, policymakers could exercise such asymmetric effects to guide the ethanol producers to be more aware of the adverse movement of corn price and its consequences. To sum up, the asymmetric impact of corn price volatility shocks should be taken into account while modeling the volatility of ethanol market.

Conclusions

In this study, we examine the role of corn market implied volatility in explaining the ethanol market returns. We also consider whether the crude oil market implied volatility can influence that effect and whether the corn market implied volatility has an asymmetric effect on the ethanol market returns. Our empirical analyses are based on conditional jump GARCH models (see also Chan and Maheu, 2002). The findings of the current study can be summarized as follows. Firstly, the corn market uncertainty, measured by the CBOT corn market implied volatility index, embodies a pivotal role in determining the price of US ethanol. This suggests that the corn market volatility is useful in predicting the returns in the US ethanol market. Since we find a strong positive connection between the US ethanol and corn markets, it implies that a rise in the corn price would cause the ethanol prices to increase. This finding is consistent with earlier studies (e.g., Kristoufek et al., 2016; Serra et al., 2011b; Chiu e al., 2016) that point towards the importance of corn market prices in regulating the US ethanol market prices. Secondly, we find a significant association between corn and ethanol markets after controlling for the effects of oil market price uncertainty. In fact, the analysis shows that the crude oil market volatility operates as a moderator in the GARCH-jump model. Thirdly, the impact of corn market implied volatility on the US ethanol market prices is found to be asymmetric. More specifically, we document that positive corn market volatility shocks have more significant influences over the ethanol market prices series than the negative ones. Finally, our analyses imply that time-varying jumps characterize the ethanol market returns.

In addition to its importance in risk assessment and risk management, an enhanced knowledge of the effect of corn market volatility on the returns of ethanol market is essential for developing effective strategies to adjust the market risk. Accordingly, our findings could help energy economists and policymakers in assessing the US ethanol market volatility. Moreover, the results of our research carry important implications for investors and traders as well. Since various financial assets are traded on the basis of ethanol and corn market prices and returns, the market participants could use our findings for making appropriate asset allocation decisions. Besides, the results could also be helpful for the purpose of hedging the risk of portfolio comprising corn and market ethanol investments. Furthermore, the future research should also explore the co-jump dynamics across the markets of corn, crude oil, and ethanol in more details.

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Table 1: Descriptive Statistics

Index →	Ethanol returns	CIV index	OVX index
Mean	-0.045886	27.41568	34.12633
Standard deviation	2.352019	7.178382	12.58391
Skewness	-0.196296	0.794648	0.560080
Kurtosis	49.61900	4.002040	2.77332
Jarque-Bera Test	127988.20***	201.3539***	74.5849***

Notes: *** indicates statistical significance at 1% level. Ethanol returns are calculated as log change of the price series.

Table 2: Results based on the GARCH-jump model represented in equations (1) – (5)

Variable	Constant intensity jump model	ARJI
π	.0315*	.0205
	(.08)	(.17)
μ_1	.1552***	.1141***
	(.00)	(.00)
μ_2	-.0500*	-.0322
	(.07)	(.26)
δ	.0151**	.0103**
	(.04)	(.03)
ω	.0793***	.0892***
	(.00)	(.00)
α	.0931***	.0814***
	(.00)	(.00)
β	.6556***	.6752***
	(.00)	(.00)
θ	-.8986***	-.1559
	(.00)	(.16)
d^2	2.4363***	1.4726***
	(.00)	(.00)
λ_0	.0659***	.0342***
	(.00)	(.00)
ρ		.8666***
		(.00)
γ		.5311***
		(.00)
Log Likelihood	-1549.69	-1611.27

Notes: δ represents the coefficient on the CIV index. The values in the parentheses indicate the *p*-values. *, ** and *** imply statistical significance at 10%, 5% and 1% levels, respectively.

Table 3: Joint effects of the CIV and OVX indexes

Variable	Constant intensity jump model	ARJI
π	.0284	.0179
	(.10)	(.28)
μ_1	.1532***	.1128***
	(.00)	(.00)
μ_2	-.0538**	-.0361
	(.04)	(.11)
δ	.0171**	.0125**
	(.03)	(.04)
ψ	.0523***	.0526***
	(.00)	(.00)
ω	.0804***	.0920***
	(.00)	(.00)
α	.0986***	.0941***
	(.00)	(.00)
β	.6407***	.6546***
	(.00)	(.00)
θ	-.8931**	-.1734**
	(.02)	(.03)
d^2	2.4772***	1.4838***
	(.00)	(.00)
λ_0	.0640***	.0361***
	(.00)	(.00)
ρ		.8748***
		(.00)
γ		.5673***
		(.00)

Notes: δ and θ represent the coefficients on the CIV index and OVX index, respectively. The values in the parentheses indicate the *p*-values. ** and *** imply statistical significance at 5% and 1% levels, respectively.

Table 4: Asymmetric impacts of the CIV index on ethanol returns

Variable	Constant intensity jump model	ARJI
π	.0086	-.0020
	(.69)	(.89)
μ_1	.1552***	.1139***
	(.00)	(.00)
μ_2	-.0520*	-.0347
	(.06)	(.18)
φ_1	.0378**	.0332***
	(.02)	(.00)
φ_2	-.0083	-.0135
	(.58)	(.24)
ω	.0809***	.0873***
	(.00)	(.00)
α	.0942***	.0814***
	(.00)	(.00)
β	.6500***	.6785***
	(.00)	(.00)
θ	-.9339***	-.1646
	(.00)	(.11)
d^2	2.4228***	1.4754***
	(.00)	(.00)
λ_0	.0657***	.0343***
	(.00)	(.00)
ρ		.8722***
		(.00)
γ		.5363***
		(.00)
Log Likelihood (Unconstrained)	-1549.69	-1611.27
Log Likelihood (Constrained)	-1547.61	-1609.33

Notes: This table indicates the results of testing the null hypothesis that CIV does not have any asymmetric impact ($H_0: \varphi_1 = \varphi_2$). The values in the parentheses indicate the *p*-values. *, ** and *** imply statistical significance at 10%, 5% and 1% levels respectively.

Table 5: Asymmetric impacts of OVX on ethanol returns

Variable	Constant intensity jump model	ARJI
π	.0514**	.0422***
	(.02)	(.00)
μ_1	.1520***	.1083***
	(.00)	(.00)
μ_2	-.0552**	-.0385
	(.04)	(.20)
ψ_1	.0685***	.0706***
	(.00)	(.00)
ψ_2	.0326**	.0295***
	(.02)	(.00)
ω	.0820***	.0919***
	(.00)	(.00)
α	.1041***	.1386***
	(.00)	(.00)
β	.6336***	.6467***
	(.00)	(.00)
θ	-.9357**	-.1441
	(.02)	(.11)
d^2	2.4828***	1.4596***
	(.00)	(.00)
λ_0	.0622***	.0339***
	(.00)	(.00)
ρ		.8724***
		(.00)
γ		.5345***
		(.00)
Log Likelihood (Unconstrained)	-1534.89	-1608.52
Log Likelihood (Constrained)	-1531.13	-1604.45

Notes: This table indicates the results of testing the null hypothesis that OVX does not have any asymmetric impact ($H_0 : \psi_1 = \psi_1$). The values in the parentheses indicate the *p*-values. ** and *** imply statistical significance at 5% and 1% levels respectively.

Table 6: Results based on the GARCH-jump model when using the return series of CIV

Variable	Constant intensity jump model	ARJI
π	.0316*	.0167
	(.09)	(.23)
μ_1	.1546***	.1087***
	(.00)	(.00)
μ_2	-.0497*	-.0343**
	(.07)	(.02)
δ	0.0082***	0.0064***
	(.00)	(.00)
ω	.0789***	.0873***
	(.00)	(.00)
α	.0931***	.0723***
	(.00)	(.00)
β	.6565***	.6727***
	(.00)	(.00)
θ	-.8905**	-.1419*
	(.02)	(.09)
d^2	2.4238***	1.4539***
	(.00)	(.00)
λ_0	.0665***	.0266***
	(.00)	(.00)
ρ		.8942***
		(.00)
γ		.4493***
		(.00)

Notes: δ represents the coefficient on the CIV returns. The values in the parentheses indicate the *p*-values. *, ** and *** imply statistical significance at 10%, 5% and 1% levels, respectively.

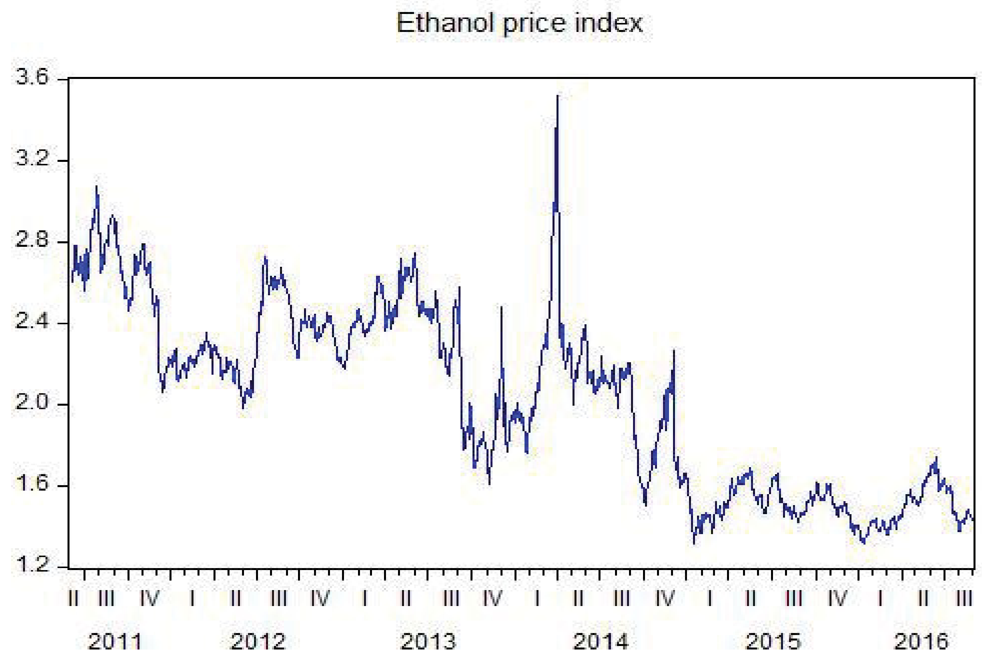
Table 7: Subsample analyses

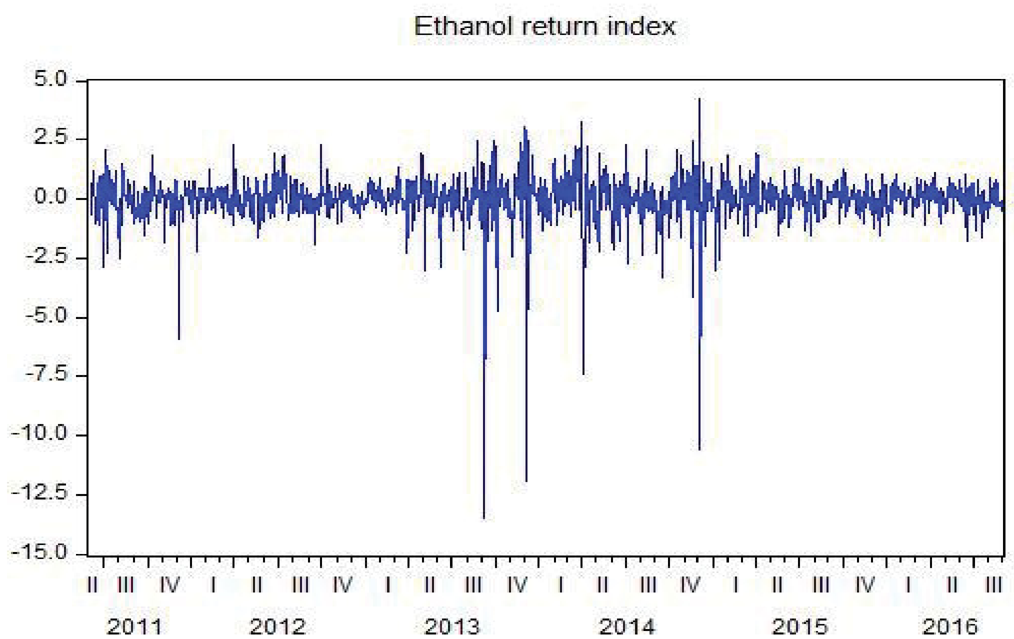
Variable	Subsample I	Subsample II
π	.0342	.0335
	(.20)	(.12)
μ_1	.1631***	.1562***
	(.00)	(.00)
μ_2	-.0987***	-.0068
	(.00)	(.76)
δ	.0358***	.0301***
	(.00)	(.00)
ω	.0738***	.1975***
	(.00)	(.00)
α	.0504**	.1222***
	(.02)	(.00)
β	.7237***	.2046***
	(.00)	(.00)
θ	-.2645	-.7851***
	(.26)	(.00)
d^2	1.4191***	2.4258***
	(.00)	(.00)
λ_0	.0894**	.0878***
	(.04)	(.00)
ρ	.5452***	.5367***
	(.00)	(.00)
γ	1.3735***	.9986***
	(.00)	(.00)

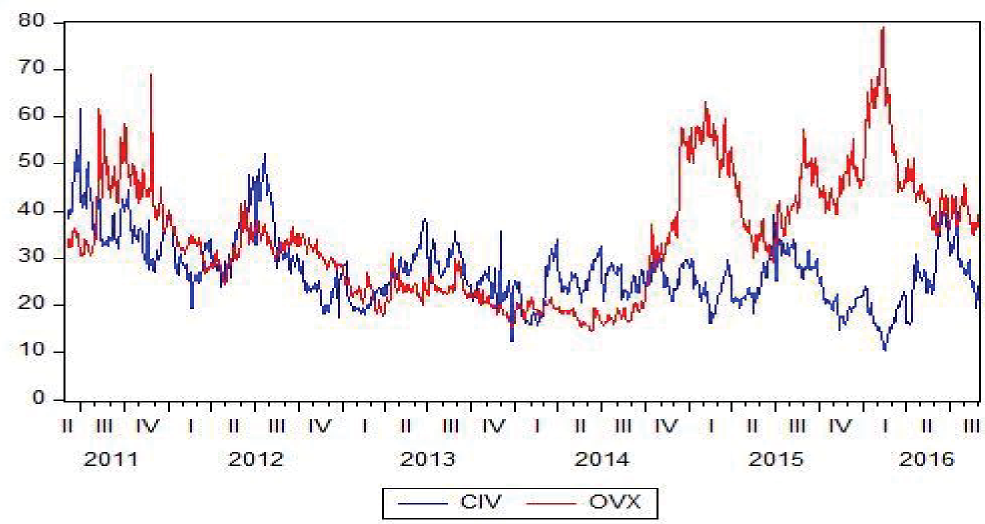
Notes: This table indicates the results of the subsample analysis. Subsample I covers the period from 2011 to 2013, while the second one ranges from 2014 to 2016. The values in the parentheses indicate the *p*-values. ** and *** imply statistical significance at 5% and 1% levels respectively.

Figure 1 Ethanol price (a) and return indexes (b)

Figure 2 Corn (CIV) and oil (OVX) VIX series for the whole sample period







80
70
60
50
40
30
20
10
0
II III IV I II III IV I II III IV I II III IV I II III IV I II III
2011 2012 2013 2014 2015 2016
CIV OVX