Market Efficiency and Optimal Hedging Strategy for the US Ethanol Market

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Abstract

In many parts of the world, the decarbonization of the energy sectors has become a priority in order to meet international climate objectives and address local pollution issues. Among these, the transportation sector always raises particular attention. Indeed, ambitious global targets may not be reachable without strong actions in the transportation sector and more generally in the mobility's framework, even if it is well-known that abatement costs in transport are high. Moreover, and because transport relies almost exclusively on fossils fuels, thinking about futures leading to a more diversified and resilient transport sector is a crucial issue. Biofuels and more particularly ethanol are considered as possible options by policy makers to decarbonize this sector. In this context the determinants of the ethanol market and the price formation process appear fundamental to better understand the dynamics of ethanol use and the possibilities for industrial players to protect themselves against price volatility. The aim of this paper is thus to study the ethanol price relationships in the US spot and futures markets. We analyze the direct and cross-hedging strategies – with corn, gasoline and oil futures markets – using wide range of linear and nonlinear specifications with an asymmetric multivariate Garch error structure. Our main results are the ability (i) of ethanol futures price to be an unbiased estimator of future spot price through the efficiency of the ethanol market, (ii) of the futures price to explain the spot price dynamics during high volatile periods as in 2008-2009 and 2013-2014 periods and (iii) of the ethanol futures market to reduce price risks exposure for long and short hedgers with the simplest strategy, i.e., the naive hedge ratio of one.

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1 Introduction

Ethanol is derived from various agricultural products (cassava, corn, hemp, sugar beet or sugarcane) and has been increasingly added to gasoline blends for several reasons: (i) it helps to reduce greenhouse gases emissions (GHG) in the transportation sector, (ii) if produced with agricultural feedstock, ethanol can be seen as a renewable energy, and (iii) from a technical point of view, the use of ethanol helps to boost octane numbers and leads to an improvement in thermal engine efficiency. All these factors have contributed to the development of ethanol's use worldwide despite some critics. Indeed, biofuels production induces an additional demand for agricultural commodities initially used for food, inducing a competition on the uses with the food (and thus potentially a rise of the prices) leading to the well-known "*food versus fuel*" debate.[1]

Despite the increase of ethanol production and consumption in the US since 2005, firms in the biofuel sector face thin profit margin in part due to the lack of risk hedging strategy to protect against energy market volatility (Cheng and Anderson, 2017). This could be one cause of some bankruptcies in this sector (Awudu et al., 2016). However, futures contracts on corn-based ethanol were launched on March 2005 on the Chicago Board of Trade (CBOT).[2] This futures market should help firms to fix spot price as the futures price can be an unbiased predictor of the future spot price (Lai and Lai, 1991). However, this property exists only under efficient market hypothesis.[3] In addition, derivatives markets, as futures contracts, allow commercial players to reduce their price risk exposure with various hedging strategies and different tools. These tools protect against adverse price movements in order to reduce the risk of loss in the business. The optimal hedging strategy is to minimize the variance of the hedge portfolio containing spot and futures contracts (Ederington, 1979). In view of links of ethanol market with corn, gasoline and oil markets, highlighted for example by Chiou-Wei et al. (2019), these latter could be used to established a cross-hedging strategy.[4]

In this context, price dynamics analysis of ethanol markets as well as the ability of the futures market to provide a good predictor of the spot price – through the market efficiency – and to hedge price risk are major challenges. Indeed, the un-

[1] This debate deals with the role of biofuels development in the increase in agricultural commodity prices during the 2000's, see, e.g., OECD (2008), Nazlioglu (2011) or Nazlioglu and Soytas (2012).

[2] CME Group is the world's leading and most diverse derivatives marketplace, made up of four markets, CME, CBOT, NYMEX, and COMEX. Each market offers a wide range of global benchmarks across major asset classes.

[3] An efficient market is characterized by prices that reflect all available information. The weak form of market efficiency considers only historical price or return series in the information set (Fama, 1970).

[4] Cross-hedging occurs when the asset underlying the contract is different than the asset whose price is being hedged (Hull, 2005).

derstanding of ethanol markets allows (i) firms to provide higher profit, (ii) ethanol market to achieve RFS2 target and (iii) policy makers to anticipate future growth of the US cellulosic biodiesel market. The literature focusing on the hedging of ethanol is very scarce with only works of Franken and Parcell (2003), Dahlgran (2009) and Spencer et al. (2018). That could explain the lack of hedging behavior of ethanol refiners. In addition, these studies only use first moment estimation to compute hedge ratio while an abundant literature highlights the performance of second moment estimation to derive efficient hedge ratio (Kroner and Sultan, 1993; Garcia et al., 1995; Kavussanos and Nomikos, 2000).

The contributions of this paper are thus fourfold. First, we study the long-term relationship between ethanol spot prices and the prices of futures contracts on the CBOT; allowing us to investigate the weak form of the efficient market hypothesis. Spencer et al. (2018) highlight such a cointegration relationship but only with the Engle and Granger (1987) specification and without providing results about long-term coefficients. Coefficients are yet useful to analysis the long-term condition in the spot market. Indeed, a long-term parameter between spot and futures prices greater (resp. smaller) than unity highlights a persistent contango (resp. backwardation) situation (Figuerola-Ferretti and Gonzalo, 2010). Our second contribution is to analyze ethanol spot and futures prices relationship in order to check the existence of financial drivers in the spot price evolution in addition to physical drivers as agricultural and energy prices. Third, we extend the scarce literature about hedging strategy in ethanol market in two ways (i) using a wider range of econometric tools than previous works and (ii) checking efficiency of more ethanol linked markets in cross-hedging strategy than previously, i.e., gasoline, oil and corn. By this, we extent previous works of Franken and Parcell (2003) – analyzing cross-hedging strategy with gasoline markets –, Dahlgran (2009) – who compares this cross-hedging strategy with direct hedging – and Spencer et al. (2018) focusing only on direct hedging strategy. Fourth, we propose a methodological contribution proposing to test benefits from the nonparametric cointegration procedure from Nielsen (2010) in prices dynamics analysis and hedging strategy. Indeed, the cointegration approach of Johansen (1988) could generate a bias in estimations due to hypothesis about the short-term specification.[5]

Our results highlight the ability of ethanol futures price to be an unbiased estimator of future spot price through the efficiency of the ethanol market and a one to one parity between these two prices in the long-term. In addition, despite the disconnection of these two markets during normal periods, futures price can help to understand the spot price dynamics during high volatile periods. These volatile periods are furthermore mainly concentrated in 2008-2009 and 2013-2014 periods. Finally, the ethanol futures market is the best one to reduce price risks exposure for long and short hedgers with the simplest strategy, i.e., the naive hedge ratio of one

[5]In particular, this procedure imposes the restriction of linearity in the short-run dynamics.

and the nonparametric cointegration from Nielsen (2010) does not provide significant improvement in comparison with the framework from Johansen (1988) despite a better explanatory power.

The rest of the paper is organized as follows. Section 2 reminds the US ethanol market evolution while section 3 briefly reviews the literature on storable commodity market efficiency and hedging strategies on energy markets with a particular focus on ethanol markets as well as methodology. In section 4, we present data and the econometric methodology. Section 5 presents empirical results. The main conclusions are summarized in the final section.

2 Ethanol market overview

Ethanol policy is a story that has many chapters in the past 40 years in the USA. Ethanol inclusion in the US gasoline blends began in 1908 when the Model-T Ford could be customized to run on gasoline or alcohol. It was not until the late Seventies, however, that the meaningful inclusion of ethanol came about. The first government involvement for ethanol was the Energy Tax Act of 1978 (a tax exemption for adding ethanol to the gasoline blend) in the wake of geopolitical concerns in the oil market with the 2$^{\text{nd}}$ world oil shock. The Surface Transportation Assistance Act of 1982 and the Tax Reform Act of 1984 gave an impetus for ethanol inclusion despite a decrease of the tax exemption during the 1992-2000 period with the Omnibus Budget Reconciliation Act of 1990. The Renewable Fuel Standard (RFS) program, created by the Energy Policy Act of 2005 and extended by the Energy Independence and Security Act of 2007, has led to a new expansion of the US ethanol market. Ethanol production (resp. consumption) have since been multiplied by four between 2005 and 2017, increasing approximately from 3.9 (resp. 4) to 15.9 (resp. 14.5) billion gallons.[6]

Since 2010 the US has become a net exporter in the ethanol market. According to the US Census Bureau, the Department of Commerce, and the Department of Agriculture, the US exported 1.4 billion gallons of ethanol in 2017 (8.65% of total US ethanol production) and imported 76.6 million gallons of fuel ethanol (less than 1% of US ethanol consumption). Brazil (33% of US exports), Canada (24%), India (13%) and Philippines (5%) are the top destinations of US ethanol in 2017. Brazil also remains the only one supplier for the US in 2017. This export-import structure within the ethanol market with Brazil can be easily explained by the RFS and California Low Carbon Fuel Standard (LCFS) targets put in place for the reduction of GHG emissions that impose more stringent requirements. Life cycle analysis (LCA) studies demonstrate that ethanol from sugarcane has a better scoring in terms of GHG

[6]These data come from US Energy Information Administration and include denaturant.

emissions than products based on corn feedstock.[7] It contributes to the substitution of corn-ethanol production from the countryside with imported sugarcane-ethanol from Brazil.

Note that the Renewable Fuel Standard (RFS2) requires the increase in the US biofuel consumption to 36 billion gallons in 2022 including a domestic production of approximately 20 billion gallons of ethanol. Corn-based ethanol consumption will be limited to 15 billion gallons corn-based ethanol uses. The requirement of approximately 5 billion gallons of cellulosic ethanol is the main future development in the US ethanol market. In addition, 11 billion gallons – ethanol equivalent – of cellulosic diesel may be produced in the US leading to the emergence of a new US biofuel market.[8] The ethanol demand is thus partly driven by such public policies. However, ethanol prices are driven by various other determinants. Indeed, US ethanol market is inherently linked to agricultural – specifically corn – and other energy markets – in particular gasoline and oil. Since the development of ethanol production in US, these markets are interrelated with price links in long- and short-term as well as in term of volatility (see for example Zhang et al. (2009), Serra et al. (2011) or Chiou-Wei et al. (2019) and references therein). The ethanol market structure is thus driven by (i) the inclusion policy of different countries, (ii) the regulatory framework, (iii) energy prices and especially the evolution of the crude oil price, and (iv) the agricultural feedstock prices. Ethanol prices registered several ups and downs since 2008, with prices ranging from $1.25 per gallon to $4.12 per gallon following the volatility observed in energy and agricultural prices.

With the development of the physical ethanol market, futures contracts on corn-based ethanol were launched by the CBOT on floor-based trading in March 2005 and on the electronic platform in 2006.[9] On the one hand, the volume reached 1,000 contracts for the first time in July 2006 and it really took off after 2009 increasing, for the two months term contract, from around 78,864 in 2008 to 404,133 in 2016, i.e., multiplied by a factor of 5 (Figure 1). We also observed a decrease in transaction volumes between 2008 and 2016 as contract terms grew longer, and a virtual absence of liquidity for long-term contracts (compared to short-term maturity). In fact, the inadequate information available at any given moment t on contracts whose maturity period is greater than ten months does not give traders the incentives to trade in the market. Moreover the maturity greater than two months registered a sharp decline in transaction volumes after 2012. On the other hand, the share of non-commercial players increased from around 15% before 2008 to over 35% on average since 2014 (Figure 2). However, both the increase in the volume of transactions on financial trading floors and the growing share of non-commercial players should be kept in perspective. During previous decades, and especially in the initial phase of construction

[7]See, for example, Edwards et al. (2014).

[8]40 CFR Part 80, 2010.

[9]For the sake of completeness, the CBOT introduced options contracts in 2007.

of the ethanol futures market, the main objective was to attract and concentrate the liquidity required for commercial traders to achieve hedging activities. Nevertheless, the rise in transaction volumes has been accompanied by a concentration of traders' liquidity on the shortest maturity contracts exchanged on commodity markets. This factor has been observed and studied, for example on the WTI market in the US (Hache and Lantz, 2013).[10]

Figure 1: Open interest by contracts maturity

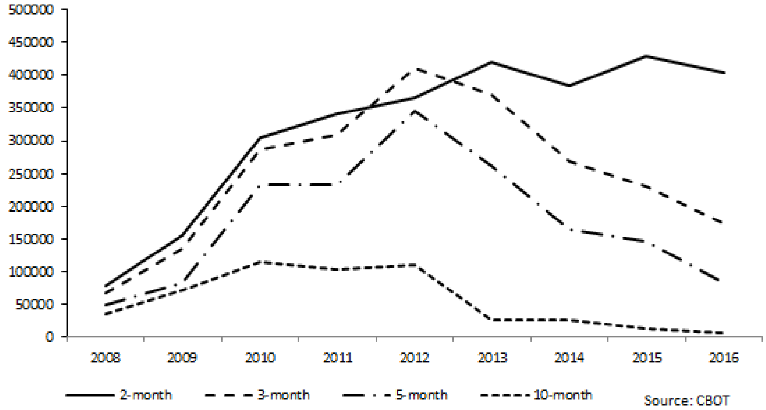
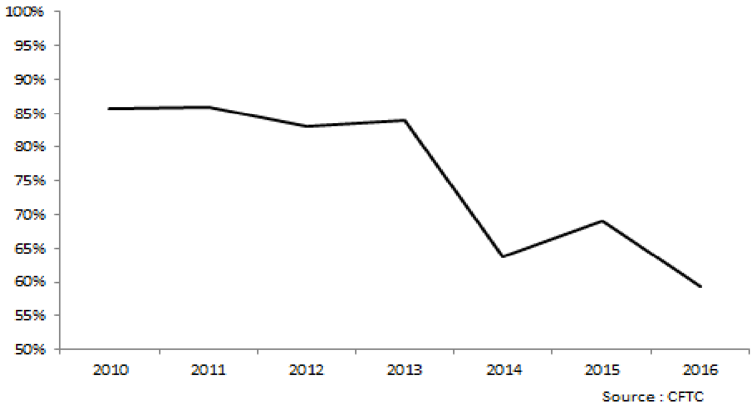


Figure 2: Commercial positions



3 Literature review

[10] See also the literature review in Lautier (2005).

Following the works of Kaldor (1939), Working (1948), Brennan (1958) and Telser (1958), spot and futures prices of a storable commodity should be equal. The difference between these prices is explained by the cost of storage and the interest rate as,

$$F_t^T = S_t exp[(r_t + \bar{s})(T - t)] \tag{1}$$

and with a log-transformation,

$$f_t^T = s_t + (r_t + \bar{s})(T - t) \tag{2}$$

Here, F_t^T (resp. f_t^T) is the price (resp. log-price) of futures contract at the time t for a maturity T. S_t (resp. s_t) is the spot price (resp. log-price) at the same date. r_t and $\bar{s}$ refer to the risk-free interest rate and the cost of carry, respectively. This latter is supposed to be constant. According to the aforementioned works, the difference between spot and futures prices is instantaneously compensated by arbitrageurs.

This hypothesis has been relaxed by Garbade and Silber (1983). They mention that arbitrageurs operate in the markets if the spread between these prices is large enough to enlarge their profits according to the transaction and information costs. Therefore, the unit relationship between spot and futures prices is only valid in the long-term. The spot and futures markets are thus efficient if prices are cointegrated as in Chowdhury (1991) or Lai and Lai (1991). In addition, Garbade and Silber (1983) show that futures markets integrate new information faster than in the underlying spot market, leading to a causality from futures to spot prices. It helps the price discovery process registered in commodities markets which leads to informational efficiency for physical and financial markets.

Figuerola-Ferretti and Gonzalo (2010) extent this model by integrating the convenience yield, i.e., the premium attributed by agents for physically holding the commodity instead of holding a futures contract. It depends on various market characteristics in the spot market (weather conditions, geopolitical unrest, transaction costs, etc.).[11] With a constant free-risk interest rate, one-period futures contract and the approximation of the convenience yield, y_t, used by these authors, as

$$y_t = \gamma_1 s_t - \gamma_2 f_t \tag{3}$$

equation (2) becomes

$$f_t = \frac{1 - \gamma_1}{1 - \gamma_2} s_t + \frac{\bar{r} + \bar{s}}{1 - \gamma_2} \tag{4}$$

Their theoretical framework allows a long-term relationship, i.e., a cointegrating relationship, with a non-unit coefficient between spot and futures prices. In addition, they mention that the coefficient value depends on the spot market condition. The

[11] See Routledge et al. (2000) or Heaney (2002) for more details on the convenience yield.

parameter is greater (resp. smaller) than unity if the spot market is in contango (resp. backwardation).

Literature about the estimation of an optimal hedge ratio has been developed since the seminal work of Ederington (1979) who proposes to use the estimated coefficient between changes in spot and futures prices with an ordinary least square estimator (OLS). However, this hedge ratio is unsatisfactory for many markets (Cecchetti et al., 1988; Myers and Thompson, 1989). Baillie and Myers (1991) and Kroner and Sultan (1993) state that the hedge ratio should be time-varying based on the time-varying distribution of many asset prices. They propose computing this dynamic optimal hedge ratio (δ_t) for each period by taking into account all past information (Ω_{t-1}) such as

$$\delta_t|\Omega_{t-1} = \frac{\sigma_{t-1}(\Delta F_{t-1}, \Delta S_{t-1})}{\sigma^2_{t-1}(\Delta F_{t-1})} \tag{5}$$

Many studies estimate those conditional covariance (σ_{t-1}) and variance (σ^2_{t-1}) with the multivariate Garch model proposed by Engle and Kroner (1995) as, for instance, Kroner and Sultan (1993), Garcia et al. (1995) or Kavussanos and Nomikos (2000) and conclude there has been an improvement of the hedging strategy with the dynamic hedge ratio compared to the constant formulation. The improvement degree depends on the market and the futures maturity studied (Lien and Tse, 2002).

The estimation of the dynamic hedge ratio should integrate the possible existence of a cointegrating relationship between spot and futures prices. Kroner and Sultan (1993), Ghosh (1993), Chou et al. (1996) or Lien (1996) highlighted an underestimated hedge ratio if this characteristic is not accounted for. In addition, Brooks et al. (2002) show the improvements of the hedge ratio effectiveness with the integration of the asymmetric volatility response against positive and negative shocks, i.e., the leverage effect. Furthermore, the conditional mean (Sarno and Valente, 2000) and variance (Lamoureux and Lastrapes, 1990) estimations can be biased if regime shifts exist. Thus, the hedge ratio effectiveness can be improved by integrating regime shifts in the estimation. Lee and Yoder (2007a,b) include regime shifts in the variance process and show an improvement – but not always significant – of the hedge ratio effectiveness. Alizadeh et al. (2008) extent this model by integrating regime shifts in variance and conditional mean processes and highlight a significant effectiveness improvement for most of the markets studied. Finally, Salvador and Arago (2014) propose to incorporate (i) the regime shifts, the cointegrating relationship and the leverage effect in the same model in order to estimate an optimal dynamic hedge ratio, as well as (ii) the short-run dynamics between spot and futures price changes.

The literature concerning hedging strategies on energy markets is well developed with, for instance, Lien and Yang (2008) for heating and crude oil markets, Alizadeh et al. (2008) on crude oil, unleaded gasoline and heating oil markets, Hanly (2017) with WTI and Brent crude oils, natural gas, unleaded gasoline, heating oil and gasoil. These various works highlight the performance of various sophisticated econometric models[12] in hedging strategy for majority of energy markets. However, the literature on hedging strategies on US ethanol market is very scarce. Franken and Parcell (2003) highlight the cross-hedging efficiency between ethanol spot price and unleaded gasoline futures markets, that is to say a price risk reduction compare to the situation without hedging behaviors. However, while they correct the estimation for autocorrelation and heteroscedasticity, they use the estimated coefficient between spot and futures price changes to compute hedge ratio and do not incorporate the error correction term, regime switching and time-varying variance process. Dahlgran (2009) compares direct hedging for ethanol commercial agents with cross-hedging strategy with unleaded and Reformulated Gasoline Blendstock for Oxygen Blending (RBOB gasoline) futures markets. He demonstrates that the direct hedging strategy outperforms cross-hedging for a four-week, and more, hedge horizon. However, he does not improve econometric tool to derive hedge ratio. Finally, Spencer et al. (2018) analyze direct hedging strategy using various econometric tools. They compare the classic OLS based hedge ratio with those provided by VAR and VECM estimation. They highlight the lack of hedging improvement with these two last econometric models.

4 Data and methods

As stressed above, our article deals with the relationship between the spot prices and the futures prices of ethanol. As transaction volumes have risen, in particular for the shortest maturities, we focus on the relationship between the spot prices and the prices for the two-month futures contracts. The continuous futures prices series is thus the Wednesday[13] closing prices of the second nearest contract.[14] The data studied are relative to the ethanol in the North American market: the spot price for ethanol (Argus Ethanol USGC barge/rail fob Houston)[15] and the futures prices of ethanol on the CBOT. The data cover the period from January 2008 to March 2018, corresponding to 534 weekly observations. The in-sample analysis is done for the

[12]In particular, these works use Markov-switching, asymmetric multivariate Garch and dynamic conditional correlation Garch specifications concerning the variance estimation.

[13]We use Tuesday when Wednesday is not a business day.

[14]The contract with the closest maturity is not liquid. In addition, we do not roll over to the front month contract to deal with thin trading and expiration effects, as Alizadeh et al. (2008), due to the low liquidity in maturity higher to 2 months.

[15]This price has the advantage to be located at an equal distance to most biorefineries (https://ethanolrfa.org/resources/biorefinery-locations/)

period from January 2008 to December 2016, 456 observations, and data for January 2017 to March 2018 are used for the out-of-sample analysis, corresponding to 78 observations. The prices are expressed in US dollars per gallon and are log-transformed.

Table 1 presents some descriptive statistics and tests results. Unit root tests confirm the stationarity of spot and futures prices series in their first-difference.[16] In addition, the Ljung and Box (1978) and ARCH tests confirm the presence of autocorrelation in most cases and heteroscedasticity, respectively. These characteristics justify the choice of a specification with autoregressive terms and heteroscedastic errors.

Table 1: Summary statistics and unit root tests

Variables	Level		Log-return	
	Spot	Futures	Spot	Futures
Mean	\$2.09	\$1.92	0.000	0.000
Std. errors	0.468	0.413	0.050	0.040
Skewness	0.263	0.290	0.073	-0.281
Kurtosis	2.329	1.767	6.096	4.297
ADF	0.047*	0.316	0.001*	0.001*
PP	0.093*	0.333	0.001*	0.001*
KPSS	0.001	0.001	>0.100*	>0.100*
Perron	-1.134	-1.189	/	/
	-3.8	-3.8	/	/
Q(6)	0.001	0.001	0.001	0.889
$Q^2(6)$	0.001	0.001	0.001	0.001

Note: This table reports descriptive statistics and the p-value of the unit root tests applied, i.e., Augmented Dickey and Fuller (1981) (ADF), Phillips and Perron (1988) (PP) and Kwiatkowski et al. (1992) (KPSS). The star mentions the stationarity of the variable. The Perron's lines refer to the test from Perron (1990) with the test's statistic and the critical value at a 5% significance level in the first and second line, respectively. The critical value comes from Perron and Vogelsang (1992). The null hypothesis of unit root with break is rejected if the test statistic, in absolute value, is greater than the critical value. Q(6) and $Q^2(6)$ are the p-value of the test from Ljung and Box (1978) and ARCH test (Engle, 1982) for 6^{th} order autocorrelation, respectively.

We apply the test from Johansen (1988) to check the existence of a long-term relationship with unit cointegrating vectors and to estimate the conditional mean with a Markov switching vector error correction model (Ms-VECM) within a bivariate framework. The inclusion of a multivariate generalized autoregressive conditional heteroscedasticity (MGarch) error structure allows us to compute the dynamic hedge ratio. By including a long-term equilibrium, we eliminate the bias in the hedge ratio estimation mentioned by Kroner and Sultan (1993) and Ghosh (1993). In addition, the nonlinear specification avoids estimation bias due to the existence of multiple regimes in the mean (Sarno and Valente, 2000) and variance (Lamoureux and Las-

[16] In view of the conflicting results for the spot log-price series, we apply the unit root test from Perron (1990) which confirms its non-stationarity with a break in mean on March 12 2014. We choose this test in view of series characteristics, i.e., the absence of trend and a potential break in the mean. We present results with innovational-outlier model for break date determination. Results with additional-outlier model are similar.

trapes, 1990) equations. Furthermore, the dynamic hedge ratio computed with this specification outperforms OLS hedge ratio in many energy markets (Alizadeh et al., 2008). Finally, we take into account the leverage effect within the Gjr framework.

It should be emphasized that the cointegration test of Johansen (1988) requires assumptions regarding the short-run dynamics that must follow a linear process. Using this procedure with a non-linear short-run specification may lead to bias in both cointegration test results and long-term estimations, generating in turn a bias on the short-run and conditional variance estimations. To overcome these major drawbacks, we rely on nonparametric variance ratio testing approach from Nielsen (2010) as this methodology does not require assumptions in the short-run specification.[17] The nonparametric variance ratio trace statistic is defined by

$$\Lambda_{n,r}(d_1) = T^{2d_1} \sum_{j=1}^{n-r} \lambda_j \tag{6}$$

where λ_j, $j = 1, ..., n$, are the eigenvalues, listed by increasing order, of the observed $(n \times T)$ time series matrix, r is the cointegration rank tested and d_1 is a summation parameter fixed to 0.1.[18] The eigenvalues of the price series matrix are given by the solutions of

$$|\lambda B_T - A_T| = 0 \tag{7}$$

with

$$\begin{aligned} A_T &= \sum_{t=1}^{T} Z_t Z_t' \\ B_T &= \sum_{t=1}^{T} \tilde{Z}_t \tilde{Z}_t' \end{aligned} \tag{8}$$

where $\tilde{Z}_t$ is the fractional difference of Z_t truncated by d_1. Z_t is our time series matrix after demeaning. The null hypothesis is the presence of $r - 1$ cointegration relationships. A test statistic that is greater than the critical value leads to the rejection of the null hypothesis in favor of the alternative, i.e., the existence of r cointegration relationships. In addition, the estimated cointegration coefficients are provided by the eigenvectors associated with eigenvalues and converge to their real values. Therefore, by using both cointegration approach from Johansen (1988) and Nielsen (2010), we can analyze the effect of the long-term estimation bias on the hedge ratio efficiency.

[17]For more details on the testing procedure, see Nielsen (2010).

[18]As mentioned by Nielsen (2010), the choice of $d_1 = 0.1$ maximizes the power of the test.

The Ms-VECM with Gjr-MGarch[19] error structure can be expressed by

$$\begin{aligned} \Delta X_t &= c + \Gamma_{st}\Delta X_{t-1} + \Pi_{st}X_{t-1} + \epsilon_{t,st} \\ \epsilon_{t,st} &= \begin{pmatrix} \epsilon_{s,t,st} \\ \epsilon_{f,t,st} \end{pmatrix} |\Omega_{t-1} \backsim IN(0, H_{t,st}) \end{aligned} \tag{9}$$

where $\Delta X_t = (\Delta s_t, \Delta f_t)'$ (resp. $X_{t-1} = (s_{t-1}, f_{t-1})'$) is the vector of log-returns (resp. log-price) and c is a vector of constant. Γ_{st} and Π_{st} are coefficient matrices related to short- and long-term dynamics, respectively.[20] These (2×2) matrices depend on the regime st, $st = 1, 2$. $\epsilon_{t,st}$ is a regime-dependent Gaussian white noise vector. With our multivariate Garch error structure, the error covariance matrix, $H_{t,st}$, is time- and regime-dependent.

As mentioned by Alizadeh et al. (2008), two steps are necessary to estimate this model. First, we apply the cointegration procedures from Johansen (1988) and Nielsen (2010) to obtain the long-term parameters, β, includes in the matrix $\Pi = \alpha\beta'$. The vector α contains parameters characterizing the adjustment process to the long-term equilibrium and will be estimated in the second step.

Second, we introduce regime shifts depending on an unobserved state variable st. The latter can takes two values, $st = 1, 2$, corresponding to two different regimes. This variable follows a first order Markov process with the transition probability matrix,

$$P = \begin{pmatrix} Pr\{1 \Rightarrow 1\} & Pr\{2 \Rightarrow 1\} \\ Pr\{1 \Rightarrow 2\} & Pr\{2 \Rightarrow 2\} \end{pmatrix} = \begin{pmatrix} 1 - Pr\{1 \Rightarrow 2\} & Pr\{2 \Rightarrow 1\} \\ Pr\{1 \Rightarrow 2\} & 1 - Pr\{2 \Rightarrow 1\} \end{pmatrix} \tag{10}$$

where $Pr\{1 \Rightarrow 2\}$ (resp. $Pr\{2 \Rightarrow 1\}$) is the probability that the system will shift from state 1 (resp. 2) to state 2 (resp. 1). $Pr\{1 \Rightarrow 1\}$ (resp. $Pr\{2 \Rightarrow 2\}$) is the probability that the system will stay in regime 1 (resp. regime 2). We obviously have $Pr\{1 \Rightarrow 1\} + Pr\{1 \Rightarrow 2\} = 1$ and $Pr\{2 \Rightarrow 1\} + Pr\{2 \Rightarrow 2\} = 1$. All the coefficients depend on the regime st except for the long-term coefficients, β. In the presence of a cointegrating relationship, the Π_{st} matrix is thus decomposed as $\Pi_{st} = \alpha_{st}\beta'$.

The conditional covariance matrix of error terms, $H_{t,st}$, is regime-dependent, time-varying, and follows a multivariate Garch specification with a Baba et al. (1987) framework, i.e., BEKK, as

$$H_{t,st} = C'_{st}C_{st} + A'_{st}\epsilon_{t-1}\epsilon'_{t-1}A_{st} + B'_{st}H_{t-1}B_{st} + D'_{st}\eta_{t-1}\eta'_{t-1}D_{st} \tag{11}$$

with ϵ_{t-1} and H_{t-1} being the vector of mean equation residuals and the global covariance matrix for the past period, respectively. η_{t-1} is negative past shocks, i.e.,

[19] We estimate a wide range of specifications but only detail the more complex model.

[20] We integrate only one lag in the short-run dynamics according to the information criterion BIC from Schwarz (1978) during the Johansen cointegration procedure.

$\eta_{t-1} = min(\epsilon_{t-1}, 0)$. C_{st} is a (2×2) lower triangular matrix containing regime-dependent coefficients. A_{st}, B_{st} and D_{st} are (2×2) diagonal matrices of coefficients measuring the past shock effects on the conditional covariance matrix, their persistence and the additional effect of a past negative shock, respectively. However, the conditional covariance matrix depends on the sequence of all previous regimes through H_{t-1}. With this path-dependence problem, the estimation by the maximum likelihood method is numerically infeasible. To overcome this problem, we follow the formulations of Gray (1996) and Lee and Yoder (2007b) concerning the conditional variances, h_{ss} and h_{ff}, and the conditional covariance, h_{sf}, respectively, as

$$h_{ss,t} = \pi_{1,t}(r^2_{s,1,t} + h_{ss,1,t}) + (1-\pi_{1,t})(r^2_{s,2,t} + h_{ss,2,t}) - [\pi_{1,t} r_{s,1,t} + (1-\pi_{1,t}) r_{s,2,t}]^2 \quad (12)$$

$$h_{ff,t} = \pi_{1,t}(r^2_{f,1,t} + h_{ff,1,t}) + (1-\pi_{1,t})(r^2_{f,2,t} + h_{ff,2,t}) - [\pi_{1,t} r_{f,1,t} + (1-\pi_{1,t}) r_{f,2,t}]^2 \quad (13)$$

$$\begin{aligned} h_{sf,t} = {} & \pi_{1,t}(r_{s,1,t} r_{f,1,t} + h_{sf,1,t}) + (1-\pi_{1,t})(r_{s,2,t} r_{f,2,t} + h_{sf,2,t}) \\ & -[\pi_{1,t} r_{s,1,t} + (1-\pi_{1,t}) r_{s,2,t}][\pi_{1,t} r_{f,1,t} + (1-\pi_{1,t}) r_{f,2,t}] \end{aligned} \quad (14)$$

In equations (12), (13) and (14), $\pi_{st,t}$ is the probability of being in the state st at the time t. $h_{ss,st,t}$ (resp. $h_{ff,st,t}$) is the regime-dependent variance concerning the spot (resp. futures) price at the time t and is contained in $H_{t,st}$. Similarly, $h_{sf,st,t}$ is the state-dependent covariance at the time t and is an element of the same matrix. $r_{s,st,t}$ (resp. $r_{f,st,t}$) is the regime-dependent conditional mean of the spot (resp. futures) price equation at the time t. These latter are calculated from the following equations:

$$\epsilon_{s,t} = \Delta s_t - [\pi_{1,t} r_{s,1,t} + (1-\pi_{1,t}) r_{s,2,t}] \quad (15)$$

$$\epsilon_{f,t} = \Delta f_t - [\pi_{1,t} r_{f,1,t} + (1-\pi_{1,t}) r_{f,2,t}] \quad (16)$$

This Ms-VEC model is estimated by maximizing of the likelihood function. Each state-dependent error follows a N-dimensional normal distribution with zero mean and $H_{t,st}$ covariance matrix. The global density function is a mixture of these distributions weighted by the probability of being in each regime:

$$\begin{aligned} f(X_t, \theta) = {} & \frac{\pi_{1,t}}{2\pi} |H_{t,1}|^{-\frac{1}{2}} exp(-\frac{1}{2} \epsilon'_{t,1} H^{-1}_{t,1} \epsilon_{t,1}) \\ & + \frac{\pi_{2,t}}{2\pi} |H_{t,2}|^{-\frac{1}{2}} exp(-\frac{1}{2} \epsilon'_{t,2} H^{-1}_{t,2} \epsilon_{t,2}) \end{aligned} \quad (17)$$

$$L(\theta) = \sum_{t=1}^{T} log f(X_t, \theta) \quad (18)$$

with θ denoting the parameter vector. The log-likelihood function (equation (18)) is maximized using the expectation-maximisation algorithm proposed by Dempser et al. (1977) under constraints like $\pi_{1,t} + \pi_{2,t} = 1$; $\pi_{1,t}, \pi_{2,t} \geqslant 0$.

With our specification, we can compute the dynamic hedge ratio as

$$\delta_t|\Omega_{t-1} = \frac{h_{sf,t}}{h_{ff,t}} \tag{19}$$

where $h_{sf,t}$ et $h_{ff,t}$ are forecasted for the out-of-sample analysis.

In order to analyze the hedging strategies' performance of each specification[21] we compute hedged portfolios each week and their returns variance over the sample as

$$Var(\Delta s_t - \delta_t \Delta f_t) \tag{20}$$

However, the variance of the hedged portfolio provide an incomplete risk measure in our case. Indeed, ethanol refiners are short hedgers concerned by minimizing loss in the basis $\Delta s_t - \delta_t \Delta f_t$, hereafter y_t. The semi-variance negative ($SVar.-$) is therefore the adequate measure of risk for ethanol refiners as they provide information in the loss risk:

$$SVar.- = \frac{1}{T}\sum_{t=1}^{T}(min(0, y_t))^2 \tag{21}$$

with y_t, the hedged portfolio return. We also provide the semi-variance positive ($SVar.+$) for long hedgers purpose, i.e., the ethanol blenders.

Another way to consider this benefit is the value-at-risk (VaR) at the probability p exposure providing the loss, L, for which a higher loss, l, has a probability p to occur. We calculate the VaR, for a probability 5%, using the empirical distribution of the hedge portfolio returns, as:

$$VaR_{5\%} = inf\{L \in \mathcal{R} : Pr(l > L) \leq 5\%\} \tag{22}$$

We also provide the Expected Shortfall (ES) which is a better measure of the risk in the hedged portfolio return. Indeed, the VaR gives only the minimal lost in the 5% of extreme negative case. The ES allows us to have the mean lost of these extreme events :

$$ES_{5\%} = E(y_t|y_t \leq VaR_{5\%}) \tag{23}$$

with y_t, the hedged portfolio return.

[21] We estimate 22 specifications including 8 linear and 14 nonlinear models. Specifications vary about inclusion, or not, of error correction and autoregressive terms in mean equation, asymmetry in variance equation, as well as parameters allowed to switch. In addition, we use an OLS model and a naive model, i.e., with a unit hedging ratio.

5 Empirical results

Recall that we first want to check the efficient market hypothesis. We second analyze the price dynamics between the US spot and futures ethanol markets before to third examine the volatility behaviors. We fourth compute a wide range of direct hedge ratio to provide best hedging strategy and compare its performance to cross-hedging strategy using gasoline, corn and oil.

Table 2: Cointegration tests

$$\beta_s s_t + f_t + \beta_0 = u_t$$

	Johansen (1988)	Nielsen (2010)
Cointegration Test	31.50 (25.86)	3.779 (3.710)
β_0	0.111 (0.001)	- (-)
β_f	1 (-)	1 (-)
β_s	-1.047 (0.070)	-1.0123 (-)

Note: Cointegration test lines provide the test statistic and critical values at a 1% significance level in brackets. A test statistic greater that the critical value leads to the null hypothesis reject of zero cointegrating relationship. The chosen specification is with constant and without trend. Parameters for the cointegration relationship are mentioned with the p-value, in brackets, from the LR test $\beta_0 = 0$ and $|\beta_s| = 1$. Note that constant is not provided with the procedure from Nielsen (2010).

First of all, Table 2 provides results given by cointegration tests from Johansen (1988)[22] and Nielsen (2010). As expected, these two procedures reject the null hypothesis of no cointegration relationship. The US ethanol market can therefore be seen as an efficient market in the weak form of this hypothesis. This result is in line with Spencer et al. (2018) who use the cointegration framework from Engle and Granger (1987). We can then analyze the ability of models from Garbade and Silber (1983) and Figuerola-Ferretti and Gonzalo (2010) to explain the ethanol market through the value of the long-term parameter β_s. As mentioned in the section 3, its unity – in absolute value – allows us to conclude to the lack of situation of contango or backwardation in the long-term. As reported for the LR ratio test from Johansen (1995), we cannot reject the null hypothesis of unit coefficient – in absolute term – for the long-term parameter associated to the spot price. The theory from Garbade and Silber (1983) is thus valid to explain the long-term relationship between these two ethanol markets, the physical market of ethanol does not exhibit contango or backwardation and the futures price of ethanol can therefore be seen as an unbiased predictor of the future price on the spot market (Lai and Lai, 1991) with

[22]Note that the result presented here comes from the eigenvalue statistic. Result with the trace statistic is close and available upon request

an one-to-one parity. To finish up with the long-term prices analysis, the Table 3 provides results from the long-term causality test from Toda and Yamamoto (1995). As expected, the hypothesis of no causality from spot to futures prices can not be rejected but the causal relationship from futures to spot prices can not be highlighted. This unexpected result contradicts the process of price discovery through the futures market and can be explained by (i) the existence of nonlinear long-term causality from futures to spot prices and/or (ii) a more complex causality system including corn, gasoline and oil markets. Indeed, Chiou-Wei et al. (2019) highlight a long-term relationship of ethanol price with corn, soybean and oil prices. The ethanol spot price could also be lead in the long-term by these agricultural and energy markets in addition to the futures price of ethanol.

Table 3: long-term causality tests

Spot ⇒ Futures	0.871
Futures ⇒ Spot	0.115

Note: The causality tests refer to the Toda and Yamamoto (1995) test whose null hypothesis is the absence of long-term causality. We provide p-value of the test.

Second, we analyze the short-term dynamics between spot and futures ethanol prices through the adjustments to equilibrium and effects of past price changes. We estimate the Ms-VEC model with two states applied to both the mean and the variance equations. These two states refer to low ($st = 1$) and high ($st = 2$) volatility regimes. Table 4 presents results with the Nielsen's cointegration specification.[23] Before results interpretation, two points must be discussed. While futures standardized errors have good properties, our specification fails to capture all the heteroscedasticity in the ethanol spot prices. In addition, this complex specification has no asymptotic theory. We should thus interpret coefficients significance with caution.[24]

Concerning the behavior of the spot and futures prices during periods of long-term disequilibrium – presented in the second part of the Table 4 –, only futures prices coefficients ($\alpha_{f,st}$) are significant in the low and high volatility regimes. Information about this disequilibrium are thus incorporated faster in the futures market leading this price to move in order to restore the long-term equilibrium. However, the ethanol market seems to be quite different compared to other energy markets. Indeed, spot prices in energy markets seem to restore faster long-term equilibrium than the futures prices as highlighted by Alizadeh et al. (2008) for the oil, gasoline and heating oil markets. The ethanol spot market is thus less reactive to new information than other energy market, probably due to the price-setting mechanism used as for example contractual agreements. This lack of responsiveness in the ethanol

[23]Table 4 presents results for the best model in term of explanatory power. Results concerning the 22 specifications are available upon request.

[24]P-values are thus computed numerically from the second derivatives matrix of the log likelihood allowing us to approximate the inverse of the variance-covariance matrix of parameters (as in Hamilton (1994)).

spot market is also found by Chiou-Wei et al. (2019) concerning long-term equilibrium with oil, corn and soybean prices. Note that the adjustment process is faster during the low volatility ($st = 1$) compared to high volatility ($st = 2$) periods highlighting a link between short-term prices dynamics and volatility regimes.

Table 4: Estimation results

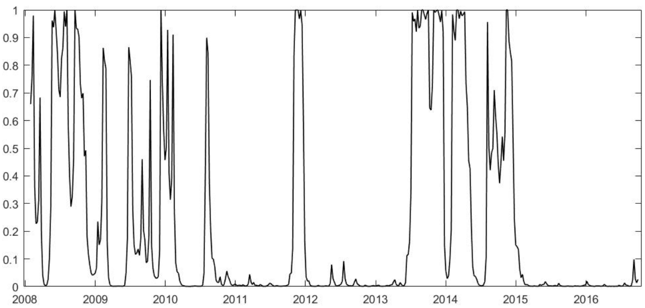
	Ms-VECM^N-Gjr-MGarch			
long-term equation				
β_s	-1.012	(-)		
β_f	1	(-)		
β_0	-	(-)		
Short term equation	$st = 1$		$st = 2$	
Adjustment to equilibrium				
$\alpha_{s,st}$	-0.001	(0.927)	-0.001	(0.955)
$\alpha_{f,st}$	**-0.117**	(0.001)	**-0.083**	(0.067)
Constant				
$c_{s,st}$	0.002	(0.500)	-0.005	(0.474)
$c_{f,st}$	**0.005**	(0.018)	**-0.012**	(0.055)
Effect of past S price variation				
$\gamma_{ss,st}$	-0.142	(0.271)	0.075	(0.606)
$\gamma_{fs,st}$	0.057	(0.640)	0.073	(0.456)
Effect of past F price variation				
$\gamma_{sf,st}$	0.233	(0.113)	**0.312**	(0.014)
$\gamma_{ff,st}$	-0.055	(0.693)	0.022	(0.881)
Variance equation	$st = 1$		$st = 2$	
Constant				
$c_{11,st}$	**0.010**	(0.024)	**0.035**	(0.001)
$c_{21,st}$	**0.029**	(0.001)	**0.036**	(0.001)
$c_{22,st}$	**0.030**	(0.001)	**0.044**	(0.001)
Effect of past variance				
$b_{11,st}$	0.229	(0.180)	0.001	(0.947)
$b_{22,st}$	0.001	(0.862)	**0.420**	(0.025)
Effect of past shocks				
$a_{11,st}$	**0.286**	(0.036)	**0.612**	(0.001)
$a_{22,st}$	0.184	(0.154)	**0.317**	(0.068)
Effect of past negative shocks				
$d_{11,st}$	**0.323**	(0.042)	**0.670**	(0.021)
$d_{22,st}$	**0.451**	(0.004)	**0.576**	(0.017)
Transition probabilities				
$Pr\{1 \Rightarrow 1\}$	**0.949**	(0.001)		
$Pr\{1 \Rightarrow 2\}$	**0.051**	(0.001)		
$Pr\{2 \Rightarrow 1\}$	**0.124**	(0.001)		
$Pr\{2 \Rightarrow 2\}$	**0.876**	(0.001)		
Diagnostics				
LogL	1.956×10^3			
	Spot	Futures		
JB	0.440	0.500		
Q(6)	0.195	0.464		
$Q^2(6)$	0.044	0.644		

Note: N refers to cointegration procedure from Nielsen (2010). For each parameter, we mention the estimated coefficients and the P-value of the Student test in bracket. The coefficient is significant at the 10% – mentioned in bold –, 5% or 1% if P-value is less than 0.10, 0.05 or 0.01, respectively. LogL, JB, Q(6) and $Q^2(6)$ are the log-likelihood, the Jarque and Bera (1980) test for normality, the Ljung and Box (1978) test for autocorrelation and the ARCH test (Engle, 1982) for heterosckedasticity, respectively.

Concerning the short-term interactions between price changes ($\gamma_{ij,st}$), these two markets seem to be disconnected during normal periods and only past changes of futures prices have a significant impact on spot prices for the high volatility state ($\gamma_{sf,2}$). This last result highlights the fact that futures market can help in understanding the ethanol spot price dynamics during periods of instability. Furthermore, the short-term interaction is also regime-dependent, confirming again the ability of our Markov-switching specification to describe it. However, the ethanol spot price could be driven by physical drivers during normal periods, mainly oil and corn prices (Chiou-Wei et al., 2019) and financial drivers during volatile periods.

Third, we now analyze results about the second moments equation as well as the evolution of the volatility. The conditional variance equation is presented in the third part of the Table 4. As expected, we note a high persistence degree ($a^2_{ii,st} + b^2_{ii,st}$) of the conditional variance during volatile periods ($st = 2$). This feature is common to oil and gasoline markets (Fong and See, 2002; Alizadeh et al., 2008). During these high volatile periods, each price variance is strongly affected by past price shocks ($a_{11,2}$ and $a_{22,2}$ for spot and futures prices, respectively) and this effect persists in the case of the futures markets as $b_{22,2}$ is significant. In addition, our specification captures well the leverage effect with high and significant coefficients $d_{ii,st}$. Losses in players' portfolio, i.e., negative shocks, have a greater impact on future conditional variance than gains, i.e., positive shocks. Shocks have more effect on variance in the high volatile periods for both positive and negative shocks.

Figure 3: Smoothed probabilities of being in a high volatility state



The second last part of the Table 4 provides probability to switch between regimes or to stay in the previous states. In addition, Figure 3 presents the probability at each time of being in the regime of high volatility.[25] The probability of switching from high to low variance states ($Pr\{2 \Rightarrow 1\}$) is greater compared to the probability of switching from low to high variance regimes ($Pr\{1 \Rightarrow 2\}$). This result indicates a shorter duration for high volatility regimes and is confirmed by the average expected

[25] We represent the smoothed probability which provides the best estimation of the states at each time using full-sample information. See Krolzig (1997) for further details on its calculation as well as on other existing probabilities.

state duration calculation proposed by Hamilton (1989).[26] Normal periods persist approximately 19.6 weeks in average while high volatility periods last 8 weeks. We can note that these periods last longer time than the oil market (Alizadeh et al., 2008). The volatility regimes in the ethanol market seem to be quite stable. During the 2008-2016 periods, only two main periods are characterized by succession of high volatility events. The first one is mainly concentrated during 2008 and 2009 and could be explained by several factors as the financial crisis, the fast development of the ethanol production and consumption since 2005 or the creation of the RFS program. The second period begins at the half 2013 and persists to the end of 2014. A reasonable explanation of the volatility in the ethanol market at this time could be the poor corn harvest in 2012 that could have impacted corn stock for ethanol producers and then ethanol prices (Spencer et al., 2018).

Table 5: In-sample direct hedging simulation

	Var.	SVar.+	SVar.+ I.	SVar.-	SVar.- I.	Util.	VaR	E.S.
No Hedged	24.42	11.76	52.1	12.56	58.5	-9.770	83,425	118,307
Naive	12.33	6.397	12.0	5.904	11.7	-4.931	61,423	86,162
OLS	12.07	6.183	8.89	5.859	11.1	-4.827	64,888	86,345
MGarch	12.27	6.131	8.11	6.118	14.8	-4.909	64,103	89,250
Gjr-MGarch	12.14	6.076	7.27	6.044	13.8	-4.857	63,890	88,681
VAR-MGarch	12.24	6.211	9.29	6.006	13.2	-4.897	63,110	87,810
VAR-Gjr-MGarch	12.05	6.063	7.08	5.965	12.6	-4.821	62,649	87,439
VECM^{J}-MGarch	12.16	6.152	8.42	5.979	12.8	-4.862	61,990	87,681
VECM^{J}-Gjr-MGarch	11.97	5.987	5.90	5.956	12.5	-4.787	62,811	87,753
VECM^{N}-MGarch	12.15	6.151	8.41	5.976	12.8	-4.860	61,996	87,712
VECM^{N}-Gjr-MGarch	11.97	5.989	5.93	5.955	12.5	-4.787	62,844	87,785
Ms-MGarch	11.71	6.077	7.29	5.608	7.06	-4.684	59,481	83,798
Ms-Gjr-MGarch	11.39	5.873	4.07	5.493	5.12	-4.556	59,952	82,620
VAR-Ms-MGarch	11.40	5.989	5.93	5.389	3.28	-4.561	57,084	81,490
VAR-Ms-Gjr-MGarch	10.92	5.652	0.32	5.243	0.58	-4.367	54,263	81,503
VECM^{J}-Ms-MGarch	11.33	5.963	5.52	5.340	2.39	-4.531	55,490	81,911
VECM^{J}-Ms-Gjr-MGarch	**10.87**	**5.634**	-	**5.212**	-	**-4.348**	55,800	81,834
VECM^{N}-Ms-MGarch	11.33	5.958	5.43	5.345	2.49	-4.531	55,603	81,978
VECM^{N}-Ms-Gjr-MGarch	10.89	5.640	0.11	5.227	0.29	-4.356	55,168	81,932
Ms-VAR-MGarch	11.63	6.195	9.05	5.413	3.71	-4.653	55,848	81,567
Ms-VAR-Gjr-MGarch	11.40	6.047	6.82	5.327	2.16	-4.559	53,679	**81,453**
Ms-VECM^{J}-MGarch	12.55	6.928	18.7	5.598	6.89	-5.021	61,127	83,684
Ms-VECM^{J}-Gjr-MGarch	11.00	5.688	0.95	5.286	1.40	-4.399	54,133	81,704
Ms-VECM^{N}-MGarch	11.54	6.076	7.28	5.437	4.13	-4.615	55,494	82,248
Ms-VECM^{N}-Gjr-MGarch	10.99	5.677	0.76	5.292	1.52	-4.397	**52,071**	81,754

Note: Variance (Var.), positive and negative Semi-Variance (SVar.+ and SVar.-) are presented in 10^{-4}. Positive and negative semi-variance improvement (SVar.+ I. and SVar.- I.) measure the incremental semi-variance reduction of the best strategy versus the other strategies. Value-at-risk (VaR) and the Expected Shorfall (ES) are in US dollars for an initial investment of $1 million. J and N refer to cointegration estimation from Johansen (1988) and Nielsen (2010), respectively.

Fourth, we can now study the hedging effectiveness of our different economic specifications as well as the various markets used for cross-hedging strategy. Let us remind that we compute the dynamic hedge ratios from conditional variance equations apart from the naive ($\delta = 1$) and the OLS hedged ratio. These latter is calculated as in Ederington (1979). Table 5 presents the various measures described in section 4. Variance is provided to give an idea of the risk reduction. The positive and negative semi-variances allow us to highlight risk reduction for long and

[26]The average expected duration of state 1 (resp. 2) can be calculated by $(Pr\{1 \Rightarrow 2\})^{-1}$ (resp. $(Pr\{2 \Rightarrow 1\})^{-1}$).

short hedgers, respectively. As we concentrate mainly our analysis on the ethanol producers, we also provide the value-at-risk and the expected shortfall for these latter, i.e., ethanol producers. We don't detail results about direct hedging in sample simulation as they only provide historical performance. Let us just mention that (i) the model using cointegration with procedure from Johansen (1988), Markov switching regime only applied on the conditional variance equations and asymmetric volatility responses (VECM$^{\mathrm{J}}$-Ms-Gjr-MGarch) is the best model for long and short hedgers, (ii) minimal value-at-risk and expected shortfall – for short hedgers – are however provided by Ms-VECM$^{\mathrm{N}}$-Gjr-MGarch and Ms-VAR-Gjr-MGarch models, respectively, and (iii) cross hedging strategies – presented in the Table 6 – have poor performance compared to direct hedging highlighting stronger links between ethanol spot and futures markets in term of second-order moment than with corn, oil and gasoline futures markets.

Table 6: Best in-sample cross hedging simulation

	Gasoline	Corn	Oil
Var.	23.02 Ms-Gjr-MGarch	20.05 VAR-Ms-Garch	21.62 Ms-Gjr-MGarch
SVar.+ (SVar.+ I.)	11.40 (50.6) Ms-Gjr-MGarch	9.548 (40.4) VAR-Ms-Garch	11.35 (50.4) Ms-VAR-Gjr-MGarch
SVar.- (SVar.- I.)	11.58 (55.0) Ms-Gjr-MGarch	10.50 (50.4) OLS	9.907 (47.4) Ms-Gjr-MGarch
VaR	76,963 VAR-Gjr-MGarch	77,280 Ms-Gjr-MGarch	67,788 Ms-Gjr-MGarch
E.S.	113,303 Ms-Gjr-MGarch	112,039 OLS	102,339 Ms-Gjr-MGarch

Note: Variance (Var.), positive and negative Semi-Variance (SVar.+ and SVar.-) are presented in 10^{-4}. Positive and negative semi-variance improvement (SVar.+ I. and SVar.- I.) measure the incremental semi-variance reduction of the best direct strategy versus the other strategies. Value-at-risk (VaR) and the Expected Shorfall (ES) are in US dollars for an initial investment of $1 million. J and N refer to cointegration estimation from Johansen (1988) and Nielsen (2010), respectively.

Table 7 presents direct hedging results with out-of-sample simulations. We can first note that all direct strategies are useful for hedging purposes as they outperform the no hedged situation at a one percent significant level. Long and short hedgers – i.e., ethanol blenders and producers, respectively – could thus use ethanol futures markets to reduce their price risk exposures. The first ones could implement the simplest strategy, with the naive hedge ratio of one, to reduce the semi-variance of 66.1%. Ethanol producers should improve their profit stability – with a reduction of 64.8% in the portfolio semi-variance – with the VECM$^{\mathrm{N}}$-Gjr-MGarch model. Note also that value-at-risk and expected shortfall are minimized by VECM$^{\mathrm{N}}$-MGarch and VAR-Gjr-MGarch, respectively. We should mention that the best strategy for short hedgers does not provide significant improvement compared to other direct hedging strategy. Ethanol producers could also use the naive hedge ratio in order to reduce the semi-variance of their hedging portfolio by 59.4% compared to the situation without hedging. The result about no significant improvement of Markov switching models in comparison to naive model is in line with oil and heating oil markets for short hedgers but not with gasoline markets (Alizadeh et al., 2008). In addition, while Spencer et al. (2018) recommend the use of OLS based hedge ratio outperforming the naive strategy during the turbulent periods, we argue that this dynamic hedging strategy does not provide hedging improvements compared to the use of a hedge ratio of 1. This latter strategy seems to improve – although without significant difference – semi-variance of 5.74% (resp. 4.04%) in short hedgers (resp. long hedgers) portfolios compared to OLS-based strategy and is the simplest tool. However, this result could be due to the out-sample period used in this analysis, i.e., October 2016 to March 2018, as the ethanol market is mainly in normal periods despite two months with low turbulence in the end of 2016 following the US presidential election results.[27] Note also that, as static strategy becomes more effective compared to complex specification as hedging horizon increases (Lien et al., 2016), the recommendation about the use of the naive hedge ratio can be extended to hedging horizon greater than one week. Finally, the use of the nonparametric cointegration procedure from Nielsen (2010) provides no systematic and significant improvement in hedging strategy in comparison to the usual tool from Johansen (1988).

Table 7: Out-sample direct hedging simulation

	Var.	SVar.+	SVar.+ I.	SVar.-	SVar.- I.	Util.	VaR	E.S.
No Hedged	11.51	5.211	66.1^{a}	6.164	64.8^{a}	-4.605	55,752	80,468
Naive	4.107	**1.767**	$-^{***}$	2.291	5.36^{***}	-1.643	43,957	54,215
OLS	4.332	1.841	4.04^{***}	2.439	11.1^{***}	-1.733	45,469	56,656
MGarch	4.119	1.827	3.31^{***}	2.243	3.33^{***}	-1.648	39,103	53,241
Gjr-MGarch	4.145	1.834	3.66^{***}	2.261	4.12^{***}	-1.658	39,943	53,801
VAR-MGarch	4.067	1.815	2.68^{***}	2.203	1.59^{***}	-1.627	39,067	53,207
VAR-Gjr-MGarch	**4.018**	1.799	1.80^{***}	2.170	0.09^{***}	**-1.607**	40,288	**53,051**
$VECM^{J}$-MGarch	4.080	1.825	3.18^{***}	2.206	1.71^{***}	-1.632	39,061	53,207
$VECM^{J}$-Gjr-MGarch	4.031	1.809	2.35^{***}	2.172	0.19^{***}	-1.612	40,558	53,147
$VECM^{N}$-MGarch	4.071	1.822	3.04^{***}	2.200	1.46^{***}	-1.629	**39,012**	53,144
$VECM^{N}$-Gjr-MGarch	4.030	1.813	2.54^{***}	**2.168**	$-^{***}$	-1.612	40,522	53,100
Ms-MGarch	4.438	1.838	3.90^{***}	2.547	14.9^{***}	-1.775	47,526	59,521
Ms-Gjr-MGarch	4.238	1.806	2.19^{***}	2.381	8.95^{***}	-1.695	47,346	57,537
VAR-Ms-MGarch	4.410	1.824	3.14^{***}	2.535	14.5^{***}	-1.764	48,607	60,477
VAR-Ms-Gjr-MGarch	4.314	1.802	1.96^{***}	2.461	11.9^{***}	-1.725	48,702	59,708
$VECM^{J}$-Ms-MGarch	4.401	1.837	3.85^{***}	2.511	13.7^{***}	-1.760	47,223	59,962
$VECM^{J}$-Ms-Gjr-MGarch	4.349	1.824	3.12^{***}	2.473	12.3^{***}	-1.740	48,297	60,025
$VECM^{N}$-Ms-MGarch	4.427	1.854	4.71^{***}	2.521	14.0^{***}	-1.771	47,400	60,300
$VECM^{N}$-Ms-Gjr-MGarch	4.350	1.835	3.73^{***}	2.463	12.0^{***}	-1.740	48,155	59,758
Ms-VAR-MGarch	4.322	1.797	1.70^{***}	2.475	12.4^{***}	-1.729	47,268	59,074
Ms-VAR-Gjr-MGarch	4.271	1.791	1.39^{***}	2.429	10.7^{***}	-1.708	47,099	58,616
Ms-$VECM^{J}$-MGarch	4.292	1.875	5.76^{***}	2.365	8.34^{***}	-1.717	42,964	55,971
Ms-$VECM^{J}$-Gjr-MGarch	4.326	1.835	3.74^{***}	2.439	11.1^{***}	-1.730	47,385	59,197
Ms-$VECM^{N}$-MGarch	4.283	1.836	3.76^{***}	2.396	9.52^{***}	-1.713	44,735	57,531
Ms-$VECM^{N}$-Gjr-MGarch	4.351	1.847	4.33^{***}	2.452	11.6^{***}	-1.740	47,498	59,577

Note: Variance (Var.), positive and negative Semi-Variance (SVar.+ and SVar.-) are presented in 10^{-4}. Positive and negative semi-variance improvement (SVar.+ I. and SVar.- I.) measure the incremental semi-variance reduction of the best strategy versus the other strategies. Value-at-risk (VaR) and the Expected Shorfall (ES) are in US dollars for an initial investment of $1 million. J and N refer to Johansen (1988) and Nielsen (2010)'s cointegration estimation, respectively. [a] indicates that the best strategy outperforms the competing model at least a 10% significance level. Stars (*, **, ***) indicate that the strategy outperforms the no hedged strategy at a 10%, 5% and 1% significance level, respectively. The P-values are provided from White (2000)'s reality check using the stationary bootstrap of Politis and Romano (1994). VaR and expected shortfall (E.S.) are in US dollars for an initial investment of $1 million. J and N refer to cointegration estimation from Johansen (1988) and Nielsen (2010), respectively.

[27] Some events during this election impacted financial markets in various sectors including the alternative energy sector (Pham et al., 2018).

Last but not least, Table 8 provides main results about out-of-sample simulation with cross hedging strategy. The best direct strategies founded in terms of positive and negative semi-variance, i.e., with hedge ratios from naive and VECM^{N}-Gjr-MGarch strategies, respectively, outperform all cross hedging strategy at least a 10% significance level. Note that this result holds using the naive hedge ratio for short hedgers. The ethanol futures market is thus the best one to use for hedge purpose in line with Dahlgran (2009) who only compares effectiveness of ethanol and gasoline futures markets. In addition, gasoline and oil futures markets seem to be inefficient for ethanol hedging activity as they do not provide significant improvements in semi-variance for long and short hedgers. However, corn futures market seems to be able to reduce price risks exposure with the naive strategy as it provides significant improvements compared to situation without hedging. However, this result is only valid for long hedgers, i.e., ethanol blenders.

Table 8: Best out-sample cross hedging simulation

	Gasoline	Corn	Oil
Var. (V. I.)	12.07 Var-MGarch	10.26 Ms-MGarch	11.68 Ms-VAR-Gjr-MGarch
SVar.+ (SVar.+ I.)	4.965 (64.4[a]) MGarch	4.115 (57.1[a*]) Naive	5.066 (65.1[a]) OLS
SVar.- (SVar.- I.)	6.744 (67.9[a]) OLS	6.001 (63.9[a]) Ms-Gjr-MGarch	6.328 (65.7[a]) Ms-VAR-Gjr-MGarch
VaR	56,486 OLS	57,058 OLS	53,891 OLS
E.S.	85,306 VECM^{N}-MGarch	83,792 OLS	83,821 VAR-MGarch

Note: Variance (Var.), positive and negative Semi-Variance (SVar.+ and SVar.-) are presented in 10^{-4}. Positive and negative semi-variance improvement (SVar.+ I. and SVar.- I.) measure the incremental semi-variance reduction of the best strategy versus the other strategies. Value-at-risk (VaR) and the Expected Shorfall (ES) are in US dollars for an initial investment of $1 million. J and N refer to Johansen (1988) and Nielsen (2010)'s cointegration estimation, respectively. [a] indicates that the best strategy outperforms the competing model at least a 10% significance level. Stars (*, **, ***) indicate that the strategy outperforms the no hedged strategy at a 10%, 5% and 1% significance level, respectively. The P-values are provided from White (2000)'s reality check using the stationary bootstrap of Politis and Romano (1994). VaR and expected shortfall (E.S.) are in US dollars for an initial investment of $1 million. J and N refer to cointegration estimation from Johansen (1988) and Nielsen (2010), respectively.

6 Conclusion

Recall that the ethanol sector is a growing market since 2005, that the ethanol producers face to thin profit margin and do not seem to use financial tools to reduce their price risks exposure, we propose an extensive study of this market with a particular focus on the spot and futures prices relationship. We thus analyze the ethanol prices dynamics in the US from 2008 to 2016 in terms of (i) long-term relationship, (ii) short-term prices dynamics, (iii) behaviors of the volatility and (iv) hedging abilities. These four first points are explored with a Markov-switching vector error correction model with an asymmetric Garch error structure. For the last one, we also apply a wide range of econometric specifications to provide the best strategy for direct hedging strategy as well as using corn, gasoline and oil futures markets to analyze cross hedging opportunities. In addition, we study the ability of the nonparametric cointegration procedure from Nielsen (2010) to improve hedge ratio estimation.

Our results show that the ethanol market is characterized by its efficiency – in the sens of the weak form of the efficient market hypothesis –, despite the lack of a clear price-discovery process from futures to spot prices in the long-term, as well as the absence of backwardation and contango. In addition, ethanol spot and futures markets is quite different from other energy markets with no responsiveness of the spot price during period of long-term disequilibrium as well as a disconnection between these two markets during normal periods. However, the futures price leads the spot price during high volatile periods. Furthermore, these latter are mainly concentrated in 2008-2009 and 2013-2014. Finally, we highlight the ability of the ethanol futures market to reduce price risks exposure with the simplest strategy, i.e., the naive hedge ratio of one, for ethanol producers and blenders. And, while corn futures market could be used by ethanol blenders to hedge purpose – in a less extent than the ethanol futures market –, it's the only cross hedging strategy providing significant improvement compared to the situation without hedging. Note also that our analysis fails to highlight significant improvement of the cointegration framework from Nielsen (2010) compared to Johansen (1988) in term of hedge ratio estimation despite the fact that it provides the best explanatory model.

This article is thus of great interest for ethanol sector as we show that the ethanol futures price provides an unbiased estimator of the future spot price, gives information of future spot price changes during high volatile periods and is an useful tool to reduce price risks exposure for market participants. However, we should keep in mind that the ethanol spot price seem to be mainly driven by physical factors during normal periods as related commodities market or environmental policies. In addition, we go further than Spencer et al. (2018) who summarize the better performance of the OLS based hedge ratio compared to complex econometric tools with "*the simple is better*" expression. Indeed, we highlight the ability of the naive strategy to provide best – or at least the same – hedging performance.

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