Efficiency Market Efficiency and optimal hedge ratio of the Ethanol Market

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Preliminary Draft
June 2017

Abstract

The aim of this paper is to study the biofuel price dynamic in the U.S. ethanol market as well as the optimal hedging strategy. By first using statistical and econometrical tools, we attempt to identify the long term relationship between ethanol spot prices and the prices of futures contracts on the Chicago Board of Trade (CBOT). Subsequently we model the short term dynamics between these two prices and on this basis with a Markov switching Vectorial Error Correction model (Ms-VECM). In addition, with a GJR-MGarch error structure, we highlight the ability of our model to outperform a large wide of specifications in hedging.

JEL Classification: Q41, Q42, G15, C41
Keywords: Ethanol prices, Future markets, Markov switching regime models, Hedge ratio

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1 Introduction

Ethanol is derived from different 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 green house gases emissions (GHG) in the transportation sector; (ii) produced with agricultural feedstock, ethanol can be seen as a renewable energy and (iii) from a technical point of view the use of ethanol boosts the octane numbers and leads to an improvement of the thermal engine efficiency. All these factors contributed to the development of ethanol's use worldwide.

After the increase of ethanol production and consumption in the U.S. in the first part of the last decade, futures contracts on corn based ethanol were launched on March, 23^{th} 2005 on the Chicago Board Of Trade. These derivatives markets allow commercial agents to reduce their price risk exposure with hedging strategy. There is an extensive literature on the optimal hedge ratio for an efficient hedging strategy with, for example, Lien and Yang (2008), Alizadeh et al. (2008), Lee (2010) or Hanly (2017) about energy markets. This hedge ratio determines the number of futures contract to buy or sell for one unit of the underlying asset to minimize variance of the hedged portfolio returns. The hedge ratio is initially defined as the estimated coefficient between spot and futures prices changes based on Ordinary Least Squares (OLS) estimation (Ederington, 1979) i.e. the ratio of the unconditional spot and futures price changes covariance over the unconditional variance of the futures price changes. It then derives from Multivariate Generalised AutoRegressive Conditional Heteroscedasticity (MGarch) model proposed by Engle and Kroner (1995) and is computed conditional second moments at each point of time (Kroner and Sultan, 1993). This dynamic hedge ratio outperforms OLS based hedge ratio by integration of new information arrivals over time.

Another feature of futures market analysed in the literature is its efficiency. First, following works of Kaldor (1939), Working (1948) Brennan (1958) and Telser (1958), among others, spot and futures prices should be equal adjusted for the cost of carry. According to this literature, the potential difference between this relationship is instantaneously compensated by arbitrageur agents. Second, Garbade and Silber (1983) relax this latter hypothesis and the unit relationship between spot and futures prices is then valid only in the long-run. Finally, Figuerola-Ferretti and Gonzalo (2010) integrate convenience yield, i.e. the premium attributed by agents to physically hold the commodity instead of holding futures contract. Their theoretical framework allows a long-term relationship with a non-unit coefficient between spot and futures prices.

Our work is constructed in two part. First, we propose an overview of U.S ethanol markets and study long-run dynamics between ethanol spot and futures prices in order to analyse the efficiency market hypothesis. Second, we compute a large wide of time-varying hedge ratios with different econometric models to look for the optimal hedging strategy for ethanol commercial agents. In addition, we analyse the ability of the gasoline futures market to hedge ethanol spot price risk. To optimize hedging strategy, we allow the spot-futures ethanol prices system to switch between two states governed by a Markov chain for both the short-run and the conditional variance processes. Hamilton (1989) proposes the Markov Switching model while Krolzig (1999)extends this specification for Vector AutoRegressive Model. By including structural breaks in the variance equation, we take into account the high volatility persistence (Lamoureux and Lastrapes, 1990). With structural breaks in the short-run dynamics, we allow for time-varying behaviour in the adjustment to the equilibrium and the short-run dynamic processes. Therefore, we include an informational link between between mean and volatility processes across each market's states (Alizadeh et al., 2008). In addition, we include asymmetric behaviour in the variance equation to take into account different responses to new information according to the past shocks sign (Brooks et al., 2002). The asymmetry is included with the GJR framework (Glosten et al., 1993). Therefore, we estimate a Markov switching Vector Error Correction model with a GJR-MGarch error structure (Ms-VECM-GJR-MGarch). Finally, we access that the use of Johansen (1988)'s cointegration procedures could lead an estimation bias. Indeed, it requires assumptions regarding the short-run dynamic whose must be a linear process while we assume a non-linear dynamic in short-run and variance equations. We propose to use the Nielsen (2010)'s non parametric cointegration procedure whose does not require model specification and we analyse its ability to improve hedging strategy.

The main contributions of this work are five-fold. First, we are able to analyse both market efficiency and dynamic hedge ratio concerning the ethanol market. To our best knowledge, our work is the first to check efficiency market hypothesis about the ethanol market. Second, we include adjustment to long-term equilibrium and regimes shifts, as Alizadeh et al. (2008), short-run dynamic between spot and futures price changes as in Salvador and Arago (2014) and asymmetric behaviour of the variance process, as Brooks et al. (2002). Third, we go further than Salvador and Arago (2014) by allow short-run dynamic between prices to be state dependent. Fourth, we propose to use the nonparametric cointegration approach of Nielsen (2010), in addition to Johansen (1988)'s cointegration, to analyse the effect of this recent approach on hedging strategy performance. Five, we check the performance of a cross-hedging strategy with the gasoline futures markets. Indeed, Franken and Parcell (2003) highlights its efficiency while Dahlgran (2009) concludes to opposite results.

In the first section, we present a brief literature review on storable commodity market efficiency and hedging-ratio estimation. In the second section, we present data and the Markov switching Vector Error Correction model (Ms-VECM-GJR-MGarch). The third section overviews the U.S. ethanol market and analyses its efficiency. The fourth section presents empirical results about optimal hedging strategy. The main conclusions are summarised in the final section.

2 A brief overview of literature

Following 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). r_t and $\bar{s}$ refer to the risk-free interest rate and the cost of carry supposed constant, respectively. According to this literature, the potential difference between this relationship is instantaneously compensated by arbitrageur agents.

The hypothesis of an instantaneous compensation by the arbitrageur agents activities is relaxed by Garbade and Silber (1983). They mention that the unit relationship between spot and futures prices are valid only in the long-term. Arbitrageur agents operate on the markets only if the spread between these prices is large enough. The elasticity of their action to the spread depends on the cost of carry, the transaction costs, etc. In addition, they show that new information is integrated by futures market faster than the underlying spot market leading to a causality from futures to spot prices, despite some reverse information flows. These feature is call the price discovery role of futures market or the informational efficiency.

Figuerola-Ferretti and Gonzalo (2010) extent this theory by integrating the convenience yield, i.e. the premium attributed by agents to physically hold the commodity instead of holding futures contract. It depends on various markets characteristics as spot market condition, transaction costs or cost of carrying commodity, among others.[1] 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

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

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

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 with a non-unit coefficient between spot and futures prices. In addition, they mention that the coefficient value depend on the spot market condition. The 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) in which he proposes to use the estimated coefficient between changes in spot and future prices with Ordinary Least Square estimator. However, this hedge ratio is unsatisfactory for some 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 to compute this dynamic optimal hedge ratio for each period by taking into account all past information 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 this dynamic hedge ratio with 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). Some studies show an improvement of this dynamic hedge ratio compared to the constant formulation with a improvement degree depending on the market and the futures maturity studied (Lien and Tse, 2002).

In addition, 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 integrated. 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 leveraged effect. Furthermore, the conditional mean (Sarno and Valente, 2000) and variance (Lamoureux and Lastrapes, 1990) estimations can be biased if regime shifts exist. Thus, an improvement of the hedge ratio effectiveness can be done by integrating regime shifts in the estimation. Lee and Yoder (2007a), Lee and Yoder (2007b) include regime shifts in the variance process and show an improvement – but not 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 the regime shifts, the cointegrating relationship and the leveraged effect in the same model in order to estimate an optimal dynamic hedge ratio. In addition, they incorporate the short-run dynamic between spot and futures price changes.

The literature concerning hedging strategy is well developed about energy markets with, for instance, Lien and Yang (2008) for heating and crude oils markets, Alizadeh et al. (2008) about the crude oil, unleaded gasoline and heating oil markets, Hanly (2017) with WTI and Brent crude oils, natural gas, unleaded gasoline, heating oil and gasoil. However, hedging literature about ethanol market is very scarce. Franken and Parcell (2003) highlight the cross-hedging efficiency between ethanol spot price and unleaded gasoline futures markets. However, while they correct estimation about autocorrelation and heteroscedasticity, they do not incorporate error correction term, regime switching and time-varying variance process. Finally, Dahlgran (2009) compares direct hedging for ethanol commercial agents with cross-hedging strategy with unleaded and RBOB gasoline futures markets. He shows that the direct hedging strategy outperforms cross-hedging for four-week, and more, hedge horizon.

3 Data and methodology

The econometric analysis covers the relationship between the spot price and the futures price of ethanol. As transaction volumes have risen, in particular for the shortest terms, we have focussed on the relationship between the spot price and the price for two-month forward contracts. The data studied are related to the ethanol on the North American market: the spot price for ethanol (Ethanol USGC barge/rail fob Houston), the futures price on the Chicago Board of Trade (CBOT) as well as the transaction volumes and open interest in the same market. Except the spot price of ethanol coming from Argus, these pieces of information are all in the public domain, and were drawn from the U.S. Energy Information Administration, from the CBOT and from the weekly market business reports of the Commodity Futures Trading Commission (CFTC). The data cover the period from July 2008 to December 2016. The sample thus contains 468 weekly observations. The prices are expressed in U.S. dollars per gallon and are log-transformed. Table 1 presents some descriptive statistics and main tests results. During the studied period, the spot and futures prices series have a mean of 0.73 and 0.65, i.e. 2.08 and 1.91 dollars per gallon, and a standard errors of 0.22 and 0.21. Unit root tests conclude to the stationarity of spot and futures prices series in their first-difference. In view of conflicting results for spot price series in level, we apply the Perron (1990)'s unit root test[2] whose confirms its non-stationarity with a break in mean on March, 12^{th} 2014. In addition, the Ljung-Box (1978)'s test confirms the presence of autocorrelation in

[2]We choose this test in view of series characteristics, i.e. the absence of trend and a potential break in mean. We present results with Innovational-Outlier model for break date determination. Results with Additional-Outlier model are close.

most cases. Finally, the ARCH test conclude to the presence of heteroscedasticity. The last two results justify the choice of a specification with autoregressive terms and heteroscedastic errors.

Table 1: Summary statistics and unit root test

Variables	Levels		First-differences	
	Spot	Futures	Spot	Futures
Mean	0.730	0.649	0.000	0.000
Std. errors	0.221	0.210	0.050	0.040
Skewness	-0.010	0.135	0.047	-0.283
Kurtosis	1.831	1.625	6.039	4.288
ADF	0.047*	0.297	0.001*	0.001*
PP	0.099*	0.306	0.001*	0.001*
KPSS	0.010	0.010	0.100*	0.100*
Perron	-1.148	-1.229	/	/
	-3.8	-3.8	/	/
Q(6)	0.001	0.001	0.001	0.681
$Q^2(6)$	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-Fuller (1981)'s test (ADF), Phillips and Perron (1988)'s test (PP) and Kwiatkowski et al. (1992)'s test (KPSS). The Perron's line refers to the Perron(1990)'s test 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 statistics is greater than the critical value. The star mentions the stationarity of the variable. Q(6) and $Q^2(6)$ are the p-value of the Ljung-Box (1978)'s test and ARCH test (Engle, 1982) for 6^{th} order autocorrelation.

We apply the Johansen (1988)'s test to check the existence of a long-term relationship with unit cointegrating vector and 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 heteroscedasticy error structure allows us to compute the dynamic hedge ratio. By including a long-term equilibrium, we eliminate a bias in the hedge ratio estimation mentioned by Kroner and Sultan (1993) and Ghosh (1993). In addition, the non-linear specification avoids estimation bias due to the existence of multiple regimes in the mean (Sarno and Valente, 2000) and variance (Lamoureux and Lastrapes, 1990) equations. Finally, the dynamic hedge ratio computed with this specification outperforms OLS hedge ratio in many energy markets (Alizadeh et al., 2008).

However, the Johansen (1988)'s cointegration tests requires assumptions regarding the short-run dynamic whose is a linear process. By using Johansen (1988)'s test and estimation procedure with a non-linear short-run specification, we risk obtaining bias on both cointegration test results and long-term estimations leading to bias on the short-run and conditional variance estimations. Therefore, we propose to use the Nielsen (2010)'s nonparametric variance ratio testing approach. This methodology does not require assumptions on the short-run specification.[3] The nonparametric

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

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.[4] The eigenvalues of the price series matrix is 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 $\tilde{Z}$ is the fractional difference of Z truncated by d_1. Z is our time series matrix after demeaning. The null hypothesis is the presence of $r-1$ cointegration relationships. A test statistic greater than the critical value leads to the reject 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 Johansen (1988) and Nielsen (2010)'s cointegration approach, we can analyze the effect of the long-term estimation bias on the hedge ratio efficiency.

The Ms-VECM with GJR-MGarch[5] 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. $\Gamma_{i,st}$ et Π_{st} are coefficient matrices related on short- and long-term dynamics, respectively. These 2×2 matrices depend on the regime st, $st = 1, 2$. $\epsilon_{t,st}$ is a regime dependant Gaussian white noise vector. With our multivariate Garch error structure, the error covariance matrix, $H_{t,st}$, is time- and regime-dependant.

As mentioned by Alizadeh et al. (2008), two steps are necessary to estimate this model. First, we check the existence of a cointegrating relationship between spot

[4]As mentioned by Nielsen (2010), the choice of $d_1 = 0.1$ maximizes the power of the test.
[5]We estimate a wide range of models but detail only the best model.

and futures prices. Considering a linear process, we apply the Johansen (1988)'s test. The λ_{max} and λ_{trace} statistics allow us to check the rank of the matrix Π. Under the null hypothesis, this rank is null and there is no cointegrating relationship. Under the alternative hypothesis, there is at least one cointegrating relationship.[6] If the rank of the long-term adjustment is non null, Π can be decomposed such as $\Pi = \alpha\beta'$. The vectors α and β are (2×1) coefficient vectors referring to the error correction coefficients, i.e. characterizing the adjustment process to the long-term equilibrium, and the long-term coefficients, describing the long-term equilibrium, respectively. In addition, we apply the likelihood ratio test from Johansen (1995) to check the existence of unitary long-term coefficients between spot and futures prices. The non reject of the null hypothesis of unit coefficient will approve the Garbade and Silber (1983)'s model against that proposed by Figuerola-Ferretti and Gonzalo (2010).

Second, we introduce regime shifts depending on an unobserved state variable st. This one 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,

$$P = \begin{pmatrix} P_{11} & P_{21} \\ P_{12} & P_{22} \end{pmatrix} = \begin{pmatrix} 1 - P_{12} & P_{21} \\ P_{12} & 1 - P_{21} \end{pmatrix} \tag{10}$$

where P_{12} (resp. P_{21}) is the probability that the system shifts from the state 1 (resp. 2) to the state 2 (resp. 1). P_{11} and P_{22} are the probabilities that the system stays in the past regime, i.e. 1 and 2, respectively. We have obviously $P_{11} + P_{12} = 1$ and $P_{21} + P_{22} = 1$. All the coefficients depend on the regime st except the long-term coefficients, β. Indeed, variables having a nonlinear cointegrating relationship do not admit an error correction model (Gonzalo and Pitarakis, 2006). In presence of a cointegrating relationship, the Π_{st} matrix is decomposed as $\Pi_{st} = \alpha_{st}\beta'$.

The conditional covariance matrix of error terms, $H_{t,st}$, is regime dependant, time-varying and follows a multivariate Garch specification with 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. $\eta_{t-1} = min(\epsilon_{t-1}, 0)$. C_{st} is a 2×2 lower triangular matrix containing regime depend 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

[6] Note that only one cointegrating relationship can exist between two series.

is numerically infeasible. To overcome this problem, we follows the formulations of Gray (1996) and Lee and Yoder (2007a) 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 to be in the state st at the time t. $h_{ss,st,t}$ (resp. $h_{ff,st,t}$) is the regime dependant variance concerning the spot (resp. futures) price at the time t and is contained into $H_{st,t}$. Similarly, $h_{sf,st,t}$ is the state dependant 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 dependant 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 estimate by maximisation of the likelihood function. Each state dependant error following a normal distribution with zero mean and $H_{st,t}$ covariance matrix, the global density function is a mixture of these distributions weighted by the probability to be in each regime:

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

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

with θ, the parameter vector. The log-likelihood function, expressed in the equation 18, is maximized by the Expectation-Maximisation algorithm proposed by Dempser et al. (1977) under constraints as $\pi_{1,t} + \pi_{2,t} = 1$, $\pi_{1,t} \geqslant 0$ and $\pi_{2,t} \leqslant 1$.

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

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

where $h_{sf,t-1}$ et $h_{ff,t-1}$ are defined in the equations (14) and (13), respectively.

In order to analyze hedging strategies performance of each specification[7], we compute hedged portfolios each week and their returns variance over the samples chosen as

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

In addition, as in Kroner and Sultan (1993) or Alizadeh et al. (2008) among others, we compute the hedger's utility function as

$$E_{t-1}U(\Delta s_t - \delta_t \Delta f_t) = E_{t-1}(\Delta s_t - \delta_t \Delta f_t) - k \times VAR_{t-1}(\Delta s_t - \delta_t \Delta f_t) \tag{21}$$

where k is the risk aversion degree. This utility function represents economic benefits from the hedging strategy. Another way to consider this benefit is the value-at-risk (VaR) exposure and is computed as

$$VaR = W_0[E(\Delta s_{t+1} - \delta_{t+1} \Delta f_{t+1}) + Z_\alpha \sqrt{VAR(\Delta s_{t+1} - \delta_{t+1} \Delta f_{t+1})}] \tag{22}$$

where W_0 is the initial value of the portfolio and Z_α is the normal distribution quantile.

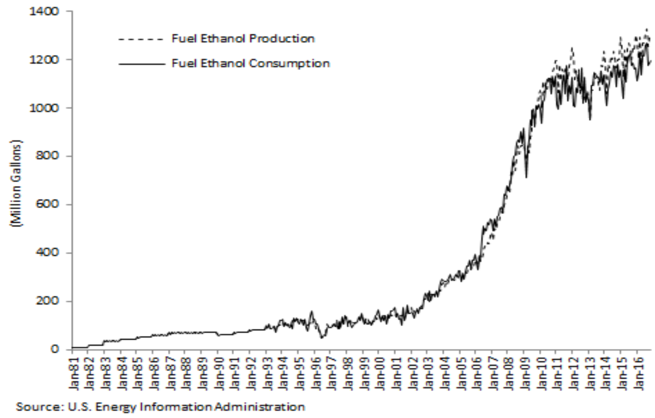
4 Ethanol market overview and efficiency hypothesis

Ethanol policy is a story with many chapters in the past 40 years in the U.S. ethanol inclusion in U.S. gasoline blends began in 1908 when the Model-T Ford could be customized to run off of gasoline or alcohol. It was not until the late seventies, however, that meaningful inclusion of ethanol came about. The first government involvement for ethanol was the Energy Tax Act of 1978 (an exemption of tax for adding ethanol in the gasoline blend) on the wake of geopolitical concerns in the oil market. The Surface Transportation Assistance Act of 1982 and the Tax Reform Act of 1984 gave an impetus of ethanol inclusion despite the decrease of the tax exemption during the 1992-2000 period with the Omnibus Budget Recollection Act. The Renewable Fuel Standard (RFS) program, created by the Energy Policy Act of 2005 and expended by the Energy Independence and Security Act of 2007, has led to the expansion of the U.S. ethanol market. The ethanol production and consumption have multiplied by four between 2005 and 2016 (Figure 1).

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

Since 2009 the U.S. became a net exporter in the ethanol market. According to the U.S. Census Bureau, Department of Commerce, and Department of Agriculture, the U.S. exported 836 million gallon of ethanol in 2015 (5.7% of total U.S. ethanol production) and imported 93 million gallons of fuel ethanol (less than 1% of U.S. ethanol consumption). Canada (30% of the U.S. exports), Brazil (14%), Philippines (9%) China (8%) and India (6%) are the top destinations of U.S. ethanol in 2015. Brazil remains also the main suppliers for the U.S. with 73% of the imported ethanol volume in 2015. This export-import structure within the ethanol market with Brazil can be easily explain by the Renewable Fuel Standard (RFS) and California Low Carbon Fuel Standard (LCFS) targets put in place for the reduction of the GHG that impose more stringent requirements. As mentioned by the Energy Information Administration[8] life cycle analysis (LCA) studies demonstrates that ethanol from sugarcane has a better scoring in terms of GHG emissions that products based on corn feedstock. It contributes to substitute corn-ethanol production from the countryside to import sugarcane-ethanol from Brazil. The ethanol market structure is already driven by the inclusion policy of the different countries, the energy prices and more especially by the evolution of the crude oil prices and by the regulatory framework. But recent changes prove that production process (ethanol is derived from different agricultural products) could also impact the international market structure and the ethanol price dynamics. The ethanol prices registered up and down since 2008 (Figure 2) and the range of prices has extended from 1.47$ per gallon to more than 4.00$ per gallon following the volatility observed during this period in the energy and agricultural prices.

Figure 1: Monthly U.S. ethanol production and consumption

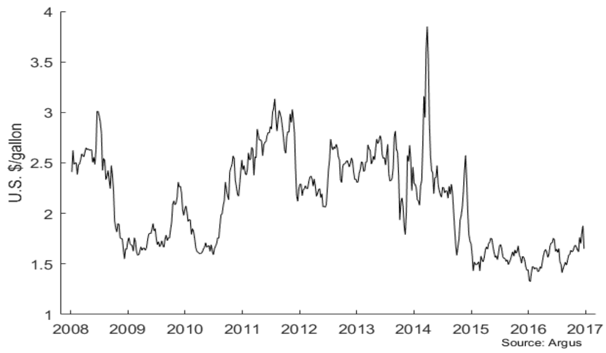


Futures contracts on corn based ethanol were launched on floor based trading on March, 23th 2005 on the CBOT and in 2006 the exchange launched the ethanol contract on electronic platform whose contributes to increase the liquidity within the market. In 2007 options contracts were also launch on the market. The volume

[8]https://www.eia.gov/todayinenergy/detail.php?id=25312

of contract reached for the first time 1 000 contracts in July 2006 and the volume of contract really took off after 2009 with the sharp increase in spot prices. During the previous decades and especially in the initial phase of construction 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 in the commodity markets. This factor has been observed and studied in the past (Lautier, 2005), and for the WTI market in the U.S. (Hache and Lantz, 2013). For ethanol futures prices, we observed between 2008 and 2016 a decrease in transaction volumes as contract terms grew longer (figure 3), 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 one year does not give traders the incentives to trade in the market. In consequence, the liquidity for distant contracts a maturity greater than 5 months decreases sharply. Moreover the maturity greater than 2 months registered a sharp decline in transaction volumes after 2012.

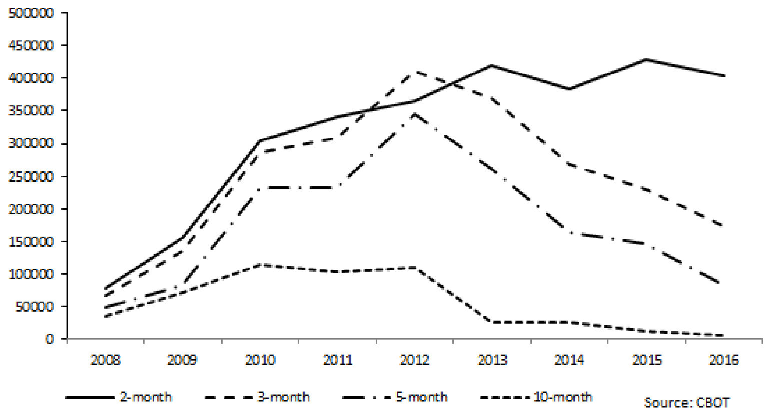
Figure 2: U.S. Ethanol spot prices



On one hand, by studying available data from 2008 to 2016, we observed a marked rise in transaction volumes for each maturity. Measured in batches of 29,000 Gallons (a standard financial contract for ethanol on the CBOT), these transactions have risen, for two-month term contracts, from around 78,864 in 2008 to 404,133 in 2016, i.e. multiplied by a factor of 5 (Figure 3). On other hand, the share of non-commercial players increased from around 15% before 2008, to over 35% on average since 2014 (Figure 4). However both the increase in the volume of transactions on financial trading floors and the increase of the share of non-commercial players should nevertheless be kept in perspective. As mentioned previously, during the previous three decades and especially in the initial phase of construction of the commodities markets, the main objective of the different derivatives marketplaces was to attract and concentrate the liquidity required for commercial traders to achieve hedging activities. In October 1974, the NYMEX launched the first energy contracts for industrial fuel oil. Simon (1984) explains the failure of this first attempt by the under-development of the financial markets and because of the very specific contract specifications (the delivery point of the futures contracts was Rotterdam and was not appealing to American commercial players). A contract for heating oil in the NYMEX was also launched in 1978 and was abandoned because of inadequate liquidity's volume. During the 1980s in the context of deregulation put in place by the Reagan administration, the NYMEX decided a simultaneous launch of energy contracts: gasoline (1981), crude oil (1983) and heating oil (1990). In Europe the International Petroleum Exchange (IPE) launched its first fuel oil contract in 1981. Since then financial markets registered both increase in term of transactions volume and also an increasing share of non-commercial players in the Exchange. In the petroleum sector competition between the two main Exchanges i.e. the Nymex in New York and the Intercontinental exchange (ICE) in London led to a strong deregulation process. In the U.S. for example the introduction at the end of December 2000 of the law modernising commodities markets, the Commodity Futures Modernization Act (CFMA), triggered market instability in the crude oil market for example (Medlock and Jaffe, 2009; Hache and Lantz, 2013).

Furthermore, the transactions' volume figures must be handled with care, for at least two reasons. The strategy of non-commercial players is partly based on managing price differentials over a certain period of time (calendar spread), between different commodities or by-products (intra or inter market spread), these activities create a high degree of fluidity for these contracts. It enables the commercial player to be able to achieve a physical arbitrage on time and enables also many non-commercial players to close their positions before the expiration of the contract.

Figure 3: Open interest by contracts maturity



In order to analyse the ability of the theories of Garbade and Silber (1983) and Figuerola-Ferretti and Gonzalo (2010) to explain the ethanol market, we ap-

Figure 4: Commercial positions

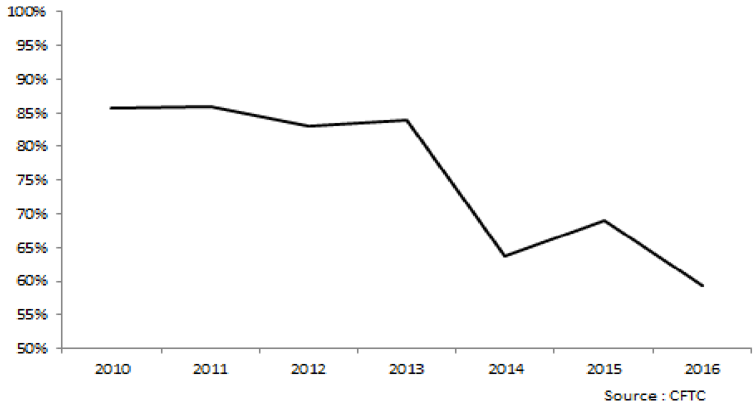
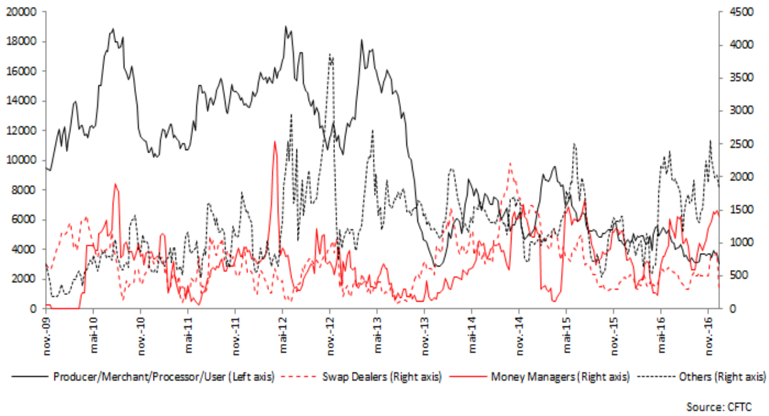


Figure 5: Position (number of contracts) by actors



ply Johansen(1988)'s cointegration tests and the Likelihood Ratio test to check the cointegrating relationship and the unit coefficient existence, respectively. Table 2 presents results confirming the presence of a long-term relationship between spot and futures ethanol prices regardless of the cointegration test used. The Likelihood Ratio test does not reject the null hypothesis of unit coefficient at a 5% significant level. Thus, the Garbade and Silber (1983)'s theory is valid to explain the long-term link between spot and futures prices on the ethanol market. Finally, the long-term causality tests conclude on a price discovery process from futures to spot prices, at a 10% significant level. With this approach, we can conclude to the market efficiency about the U.S. ethanol market.

However, the decrease in transaction volume on the ethanol future market for maturity greater than two months beginning in 2012 and in commercial agents activities for two-month contract since 2013 (Figure 5) could be explained by the results presented in Table 3. Indeed, the unit relationship between spot and futures prices

Table 2: Cointegration and causality test

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

Lags	H_0	P-value λ_{max} test	P-value λ_{trace} test	Cointegration vector (β_s 1 β_0)	LR test $H_0 : \beta_s$=-1	LR test $H_0 : \beta_0$=0
1	r=0	0.001	0.001	(-1.044 1 0.109)	0.078	0.001
-	H_0	Test stat	Critical Value	Cointegration vector	-	-
-	r=0	3.78	3.57	(-1.010 1 -)	-	-
Causality test					P-value	
Spot to Futures prices					0.867	
Futures to Spot prices					0.087	

Note: The two first lines present the Johansen (1988)'s test results. The lags column mentions the number of lag in the VEC Model. Lag length choice is based on Schwartz (1978) Information Criterion. The two P-value columns refers to the P-value of two tests mentioned. P-value inferior to 0.05 leads to the null hypothesis reject of zero cointegrating vector against one. Cointegrating vector column mentions coefficients estimated with $\hat{\beta}_s$ normalised to unity. The LR test checks the existence of an one-to-one relationship between spot and futures prices. We mention the P-value of the test. The two next lines present the Nielsen (2010)'s test results with the test statistic and the critical value associated at a 5% significance level. The chosen specification is with constant and without trend. The null hypothesis is rejected when the test statistic is superior to the critical value. Note that constant is not estimated with this procedure. The causality test refers to the Toda and Yamamoto (1995) test whose null hypothesis is the absence of long-term causality.

Table 3: Long-term coefficient for sub-samples

	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016
λ_{trace} test	0.097	0.329	0.713	0.061	0.018	0.591	0.919	0.114
$\lvert\beta_s\rvert$	0.973	0.812	0.834	1.229	0.863	3.084	0.726	0.926
$H_0 : \lvert\beta s\rvert$=1	0.159	0.002	0.027	0.001	0.001	0.012	0.132	0.001

Note: The first line mentions the P-value of the cointegration test. The second line refers to the long-term coefficient for a two-year estimation. The third line presents the P-value for the unity constraint test, c.f. note table 2.

is rejected at a 5% significant level for all two-year periods since 2009, except in 2013-2014. In addition, situations of long-run backwardation, $|\beta_s| < 1$, and contango, $|\beta_s| > 1$, alternate. These changes in market conditions could lead to the exit of many agents, especially commercial agents, from the market due to difficulties of making expectations.

5 Empirical results

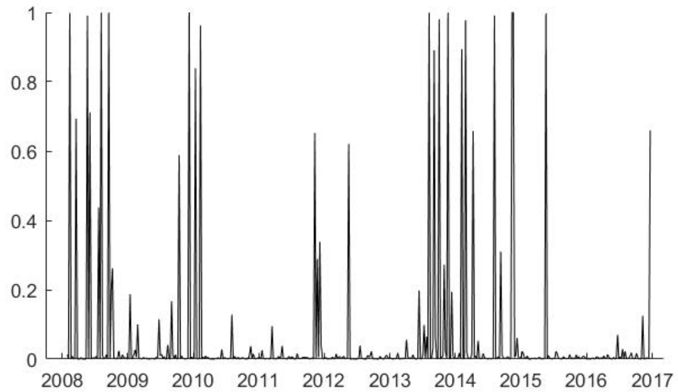
We estimate the Ms-VEC model with two states applied to both the mean and the variance equations. These two states refer to low and high volatility regime. Table 4 presents results with the Johansen's cointegration specification.[9] In each states, the futures price adjust to equilibrium more than spot prices ($|\alpha_{s,st}| < |\alpha_{f,st}|$). This result highlights the minor role of futures prices in the discovery process at short-term. In addition, during high volatility period ($st = 1$), spot prices do not adjust to equilibrium. It seems that spot market is disconnected from futures market during these periods. Note that this adjustment process is faster for each price series during low volatility regime ($st = 2$), compare to high volatility state, confirming this view. Furthermore, this result highlights that the dynamic between the ethanol spot and

[9] We present results for the best model. Other results are available upon request.

futures prices is regime dependant confirming the ability of our Markov switching specification to describe it. Concerning the short-run dynamics ($\gamma_{i,j,st}$), the spot prices depend on futures prices changes during normal periods while futures prices show very little response to spot price changes. During volatile periods, spot prices seem again partially disconnected from futures market with a higher response to its changes than to futures prices changes ($\gamma_{11,1} > \gamma_{12,2}$). Figure 6 presents probability of being in the high volatility regime.[10] Two main periods of high volatility are in 2008 and 2013-2014. The market disconnection during this two periods could be explain by the low liquidity in 2008 (Figure 3) and by few positions taken by commercial agents for the second period (Figure 5).

Turning to the conditional variance equation, the variance process is non-stationary in the high volatility state with one parameter greater than unity for each price series ($a_{11,1}$ and $d_{22,1}$). Note that spot prices variance have high reaction to (positive) shocks but no persistence during volatile periods while variance behaviour of spot and futures prices are close in low volatility periods. These results confirm again the disconnection of these two markets. Hence, it seems that commercial agents do not integrate information from ethanol futures markets during instability periods.

Figure 6: Smoothed probabilities of being in high volatility state



[10]We represent the smoothed probability whose 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 others probabilities existing.

Table 4: Estimation results of the Ms-VECM-GJR-MGarch

$$\beta_s s_t + \beta_f f_t + \beta_0 = u_t \qquad \begin{pmatrix}\Delta s_t\\ \Delta f_t\end{pmatrix} = \begin{pmatrix}c_{s,st}\\ c_{f,st}\end{pmatrix} + \begin{pmatrix}\alpha_{s,st}\\ \alpha_{f,st}\end{pmatrix} u_{t-1} + \begin{pmatrix}\gamma_{11,st} & \gamma_{12,st}\\ \gamma_{21,st} & \gamma_{22,st}\end{pmatrix}\begin{pmatrix}\Delta s_{t-1}\\ \Delta f_{t-1}\end{pmatrix} + \begin{pmatrix}\epsilon_{s,t,st}\\ \epsilon_{f,t,st}\end{pmatrix} \qquad \begin{pmatrix}\epsilon_{s,t,st}\\ \epsilon_{f,t,st}\end{pmatrix}|\Omega_{t-1} \backsim N(0, H_{t,st})$$

$$H_t = \begin{pmatrix}c_{11,st} & 0\\ c_{21,st} & c_{22,st}\end{pmatrix}'\begin{pmatrix}c_{11,st} & 0\\ c_{21,st} & c_{22,st}\end{pmatrix} + \begin{pmatrix}a_{11,st} & 0\\ 0 & a_{22,st}\end{pmatrix}'\begin{pmatrix}\epsilon_{s,t-1}\\ \epsilon_{f,t-1}\end{pmatrix}\begin{pmatrix}\epsilon_{s,t-1}\\ \epsilon_{f,t-1}\end{pmatrix}'\begin{pmatrix}a_{11,st} & 0\\ 0 & a_{22,st}\end{pmatrix} + \begin{pmatrix}b_{11,st} & 0\\ 0 & b_{22,st}\end{pmatrix}' H_{t-1}\begin{pmatrix}b_{11,st} & 0\\ 0 & b_{22,st}\end{pmatrix} + \begin{pmatrix}d_{11,st} & 0\\ 0 & d_{22,st}\end{pmatrix}'\begin{pmatrix}\eta_{s,t-1}\\ \eta_{f,t-1}\end{pmatrix}\begin{pmatrix}\eta_{s,t-1}\\ \eta_{f,t-1}\end{pmatrix}'\begin{pmatrix}d_{11,st} & 0\\ 0 & d_{22,st}\end{pmatrix}$$

Mean Equation				
β_s	-1.044	(-)		
β_f	1	(-)		
β_0	0.109	(-)		
	$st = 1$		$st = 2$	
$c_{s,st}$	-0.038	(0.001)	0.002	(0.001)
$c_{f,st}$	-0.035	(0.001)	0.004	(0.001)
$\alpha_{s,st}$	-0.001	(0.999)	-0.001	(0.069)
$\alpha_{f,st}$	-0.015	(0.019)	-0.081	(0.001)
$\gamma_{11,st}$	0.880	(0.001)	-0.255	(0.001)
$\gamma_{12,st}$	0.180	(0.001)	0.350	(0.001)
$\gamma_{21,st}$	0.247	(0.001)	-0.047	(0.001)
$\gamma_{22,st}$	-0.203	(0.001)	0.048	(0.001)
$c_{11,st}$	0.001	(0.986)	0.010	(0.001)
$c_{21,st}$	0.001	(0.988)	0.023	(0.001)
$c_{22,st}$	0.026	(0.001)	0.023	(0.001)
$a_{11,st}$	2.029	(0.001)	0.430	(0.001)
$a_{22,st}$	0.802	(0.001)	0.293	(0.001)
$b_{11,st}$	0.001	(0.999)	0.532	(0.001)
$b_{22,st}$	0.814	(0.001)	0.569	(0.001)
$d_{11,st}$	0.001	(0.988)	0.494	(0.001)
$d_{22,st}$	1.043	(0.001)	0.474	(0.001)
P_{11}	0.074	(0.001)		
P_{12}	0.926	(0.001)		
P_{21}	0.107	(0.001)		
P_{22}	0.893	(0.001)		
	spot	futures		
JB	0.001	0.011		
Q(6)	0.001	0.645		
$Q^2(6)$	0.001	0.001		

Note: For each state, we mention the estimated coefficients and the P-value of the Student test in bracket. The coefficient is significant at the 10%, 5% or 1% if p-value is less than 0.10, 0.05 or 0.01, respectively. JB, Q(6) and $Q^2(6)$ are the Bera and Jarque (1980)'s test for normality, the Ljung-Box (1978)'s test and the ARCH test (Engle, 1982), respectively.

Finally, the probability to switch from high to low variance states (P_{12}) is greater compare to the probability to switch from low to high variance regimes (P_{21}). This result indicates a shorter duration for high volatility regimes and is confirmed by the average expected state duration calculation proposed by Hamilton (1989).[11] These durations are 1.08 and 9.35 weeks for high and low volatility regimes, respectively. As mentionned above, Figure 6 presents the "smoothed" probability of being in the high variance regime. This regime is mainly apparent during the beginning of our sample, i.e. 2008, as well as during the period from the end of 2013 to mid-2014. These periods of high volatility could therefore be due to a low liquidity in the futures market (Figure 3 and 5).

Our different model specifications allow us to compute the dynamic hedge ratios. We mention also the naive ($\delta = 1$) and OLS hedge ratios of Ederington (1979). We also provide information about a non-hedged strategy for comparison. In addition, we compute cross-hedge ratios with gasoline futures market estimating from our different specifications. These latter will allow us to compare direct hedging with the ethanol futures market and cross-hedging with the gasoline futures market.[12] The gasoline market was usually used to risk hedging before the ethanol futures market beginning (Franken and Parcell, 2003).

Table 5 provides variance, utility and Value-at-Risk for each specifications and markets. During the 5/25/2016-12/21/2016 period, the optimal specification is a VAR-GJR-MGarch. The lack of high volatility state (Figure 6) and cointegration relationship (Table 3) during this period explain this results. In addition, all cross-hedging strategy underperform the situation without hedging.

Table 6 mentions results of each hedging strategies for two other panels, i.e. 1/06/2010-8/04/2010 and 1/09/2012-8/01/2012. The Ms-VECM-GJR-MGarch with Johansen's cointegration provides the best strategy for both periods. This result confirms ability of Markov switching, Johansen's cointegration, and asymmetric specifications to hedge on the ethanol market. Here, hedgers can decrease of 2,585\$ and 1.296\$ their average weekly Value-at-Risk with an initial portfolio value of 1,000,000\$ compared to the simple OLS specification. These weekly decreases correspond to 18,641\$ and 9,346\$ annualized decrease that is to say 0.18% and 0.09% of the initial portfolio value. Furthermore, cross-hedging strategies outperform the non-hedged situation for each periods with aforementioned and OLS models for panels B and C, respectively. Finally, the Johansen (1988)'s cointegration procedure outperforms the nonparametric approach of Nielsen (2010) for 10 strategies against 8 with ethanol markets as well as with cross-hedging on gasoline futures market. This result could be due at several.

[11] The average expected duration of state i can be calculated by $(P_{ij})^{-1}$.
[12] New York Harbor Reformulated RBOB Regular Gasoline.

Table 5: In-sample hedging simulation

	Ethanol Spot and Futures			Ethanol Spot and Essence Futures		
	Variance	Utility	VaR	Variance	Utility	VaR
Panel A						
No Hedged	12.818	-5.1271	59,073	12.818	-5.1271	59,073
Naive	5.6496	-2.2599	39,219	36.667	-14.667	99,912
OLS	6.0533	-2.4213	40,596	18.164	-7.2658	70,322
MGarch	5.6404	-2.2561	39,187	18.957	-7.5829	71,841
GJR-MGarch	5.7136	-2.2854	39,440	18.235	-7.2938	70,458
VAR-MGarch	5.5787	-2.2315	38,972	18.942	-7.5767	71,811
VAR-GJR-MGarch	5.5677	-2.2272	38,934	18.178	-7.2710	70,348
VECM^J-MGarch	5.5922	-2.2369	39,019	18.922	-7.5687	71,774
VECM^J-GJR-MGarch	5.6052	-2.2421	39,065	18.249	-7.2995	70,486
VECM^N-MGarch	6.1329	-2.4531	40,862	18.910	-7.5641	71,752
VECM^N-GJR-MGarch	5.6109	-2.2444	39,084	18.238	-7.2953	70,465
Ms-MGarch	5.9618	-2.3847	40,288	18.955	-7.5818	71,836
Ms-GJR-MGarch	6.1917	-2.4767	41,057	18.200	-7.2800	70,391
VAR-Ms-MGarch	5.9420	-2.3768	40,221	18.064	-7.2256	70,128
VAR-Ms-GJR-MGarch	6.4670	-2.5868	41,960	18.407	-7.3628	70,791
VECM^J-Ms-MGarch	5.9376	-2.3750	40,206	18.024	-7.2095	70,050
VECM^J-Ms-GJR-MGarch	6.5960	-2.6384	42,377	18.437	-7.3748	70,848
VECM^N-Ms-MGarch	5.9709	-2.3884	40,319	18.217	-7.2868	70,424
VECM^N-Ms-GJR-MGarch	6.6559	-2.6623	42,568	18.178	-7.2712	70,349
Ms-VAR-MGarch	5.6600	-2.2640	39,255	18.101	-7.2405	70,200
Ms-VAR-GJR-MGarch	5.7750	-2.3100	39,651	18.094	-7.2377	70,187
Ms-VECM^J-MGarch	5.8284	-2.3314	39,834	18.181	-7.2726	70,355
Ms-VECM^J-GJR-MGarch	7.3905	-2.9562	44,856	16.211	-6.4842	66,433
Ms-VECM^N-MGarch	6.4706	-2.5882	41.972	18.217	-7.2868	70,424
Ms-VECM^N-GJR-MGarch	6.4690	-2.5876	41,967	18.292	-7.3170	70,570

Note: Panel A refers to 5/25/16-12/21/16. Variance and Utility are presented in 10^{-4} and 10^{-3}, respectively. VaR is in U.S. Dollars for an initial investment of 1 million dollars and $k = 4$. J and N refer to Johansen (1988) and Nielsen (2010)'s cointegration estimation, respectively.

Table 6: In-sample hedging simulation with panel B and C

	Ethanol Spot and Futures			Ethanol Spot and Essence Futures		
	Variance	Utility	VaR	Variance	Utility	VaR
Panel B						
No Hedged	9.7736	-3.9095	51,584	9.7736	-3.9095	51,584
Naive	5.7974	-2.3189	39,728	17.870	-7.1481	69,751
OLS	5.3950	-2.1580	38,325	7.7517	-3.1007	45,939
MGarch	5.6913	-2.2765	39,363	8.0369	-3.2148	46,777
GJR-MGarch	5.6056	-2.2422	39,066	7.9168	-3.1667	46,426
VAR-MGarch	5.6121	-2.2449	39,088	8.0720	-3.2288	46,879
VAR-GJR-MGarch	5.6330	-2.2532	39,161	7.9824	-3.1930	46,618
VECM^J-MGarch	5.6170	-2.2468	39,105	8.0326	-3.2130	46,764
VECM^J-GJR-MGarch	5.6428	-2.2571	39,195	8.0642	-3.2257	46,856
VECM^N-MGarch	5.7126	-2.2851	39,437	8.0372	-3.2149	46,777
VECM^N-GJR-MGarch	5.6445	-2.2578	39,201	8.0687	-3.2275	46,869
Ms-MGarch	5.4167	-2.1667	38,402	8.0324	-3,2130	46,763
Ms-GJR-MGarch	5.3329	-2.1331	38,104	7.9821	-3.1928	46,617
VAR-Ms-MGarch	5.4635	-2.1854	38,567	7.9027	-3.1611	46,384
VAR-Ms-GJR-MGarch	5.2726	-2.1091	37,888	7.9991	-3.1996	46,666
VECM^J-Ms-MGarch	5.4717	-2.1887	38,596	7.8041	-3.1216	46,094
VECM^J-Ms-GJR-MGarch	5.2199	-2.0880	37,698	8.0956	-3.2383	46,947
VECM^N-Ms-MGarch	5.4588	-2.1835	38,551	7.7840	-3.1136	46,035
VECM^N-Ms-GJR-MGarch	5.2132	-2.0853	37,673	8.1095	-3.2438	46,987
Ms-VAR-MGarch	5.3271	-2.1308	38,083	7.8016	-3.1207	46,087
Ms-VAR-GJR-MGarch	5.5619	-2.2247	38,913	7.7725	-3.1090	46,001
Ms-VECM^J-MGarch	5.6938	-2.2775	39,372	7.9081	-3.1633	46,400
Ms-VECM^J-GJR-MGarch	4.6918	-1.8767	35,740	7.9638	-3.1855	46.563
Ms-VECM^N-MGarch	5.2964	-2.1186	37,973	7.7726	-3.1091	46,001
Ms-VECM^N-GJR-MGarch	5.3765	-2.1506	38,259	7.7695	-3.1078	45,992
Panel C						
No Hedged	10.950	-4.3801	54,600	10.950	-4.3801	54,600
Naive	3.1333	-1.2533	29,207	14.189	-5.6755	62,152
OLS	2.8496	-1.1399	27,853	11.110	-4.4439	54,996
MGarch	3.5199	-1.4080	30,956	10.882	-4.3529	54,431
GJR-MGarch	3.4138	-1.3655	30,486	11.016	-4.4063	54,763
VAR-MGarch	3.3610	-1.3444	30,249	11.125	-4.4500	55,034
VAR-GJR-MGarch	3.3093	-1.3237	30,016	11.094	-4.4375	54,957
VECM^J-MGarch	3.2879	-1.3152	29,919	10.963	-4.3853	54,633
VECM^J-GJR-MGarch	3.3420	-1.3368	30,164	10.920	-4.3681	54,525
VECM^N-MGarch	2.7996	-1.1198	27,608	10.948	-4.3791	54,594
VECM^N-GJR-MGarch	3.3355	-1.3342	20,135	10.917	-4.3669	54,518
Ms-MGarch	2.9370	-1.1748	28,277	10.869	-4.3475	54,397
Ms-GJR-MGarch	2.8212	-1.1285	27,714	11.092	-4.4366	54,952
VAR-Ms-MGarch	3.1885	-1.2754	29,463	10.866	-4.3462	54,389
VAR-Ms-GJR-MGarch	2.7448	-1.0978	27,335	10.827	-4.3308	54,292
VECM^J-Ms-MGarch	3.1765	-1.2706	29,408	10.755	-4.3020	54,111
VECM^J-Ms-GJR-MGarch	2.6695	-1.0678	26,959	10.959	-4.3836	54,622
VECM^N-Ms-MGarch	3.1552	-1.2621	29,309	10.831	-4.3325	54,303
VECM^N-Ms-GJR-MGarch	2.6451	-1.0581	26,835	10.942	-4.3768	54,580
Ms-VAR-MGarch	3.0836	-1.2334	28,974	11.004	-4.4016	54,734
Ms-VAR-GJR-MGarch	2.9279	-1.1712	28,233	10.983	-4.3931	54,681
Ms-VECM^J-MGarch	2.7052	-1.0821	27,138	11.086	-4.4343	54,937
Ms-VECM^J-GJR-MGarch	2.5905	-1.0362	26,557	10.548	-4.2194	53,589
Ms-VECM^N-MGarch	2.8455	-1.1382	27,833	10.806	-4.3225	54,240
Ms-VECM^N-GJR-MGarch	2.8925	-1.1570	28,062	10.737	-4.2952	54,068

Note: Panel B and Panel C refer to 1/06/10-8/04/10 and 1/09/12-8/01/12, respectively. Variance and Utility are presented in 10^{-4} and 10^{-3}, respectively. VaR is in U.S. Dollars for an initial investment of 1 million dollars and $k = 4$. J and N refer to Johansen (1988) and Nielsen (2010)'s cointegration estimation, respectively.

6 Conclusion

In this paper, we analyze ethanol market in two directions. First, we study the efficiency of the market with cointegration framework. Second, we provide several dynamic hedge ratios and we will be able to examine their performance with in-sample simulations. For this purpose, we use a Markov switching Vector Error Correction model with an asymmetric Garch error structure. This specification allows us to study the long-term, short-term and variance dynamics across different volatility regimes.

Our results are five-fold. First, the long-term equilibrium in the ethanol market is well explained by the Garbade and Silber (1983)'s theory about efficiency in storable commodity markets, compare to the Figuerola-Ferretti and Gonzalo (2010)'s model. In addition, the price discovery process from futures to spot prices is found in the long-term. However, the ethanol market alternates between long-term backwardation and contango since 2009. Second, ethanol spot market seems disconnected from the futures market during high volatility period, that is to say mainly in 2008 and 2013-2014. Third, direct hedging strategy outperform always a cross-hedging strategy with gasoline futures markets. Four, the Markov switching VEC model with asymmetric MGarch error process linked to Johansen(1988)'s cointegration estimation outperforms other specifications for two thirds of periods analysed. Five, although the previous mentioned cointegration procedure provides the best specification, the Nielsen (2010)'s nonparametric tools gives good results for many model specifications.

However, the few liquidity on the ethanol futures market, especially for longer maturity contract, could make more feasible a cross-hedging strategy compare to direct hedging. Research on others commodity futures market for a better cross-hedging strategy could provide best results. Crude oil or corn futures markets could provides good alternatives for cross-hedging as well as raw sugar market.

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