Efficiency market hypothesis and optimal hedge ratio of the Ethanol Market

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Abstract

The aim of this paper is to study the biofuel price dynamic in the ethanol market in the US. 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 a Markov Switching Vectorial Error Correction Model (MS-VECM) with two distinct state: a standard non-volatile state and a crisis state with volatility has been estimated. In addition we assess for each week the optimal hedge ratio in order to minimise the variance of the trader's portfolio.

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

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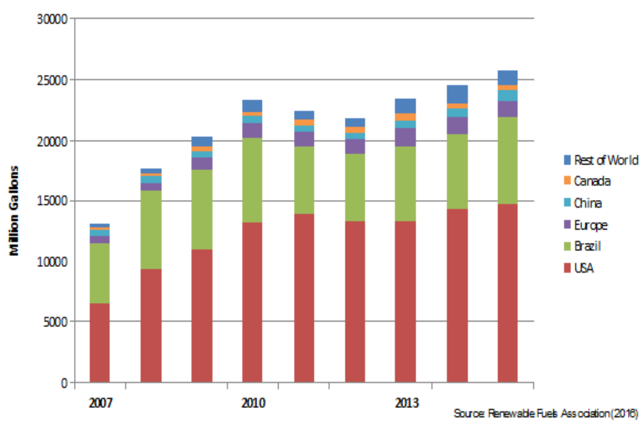
1 Introduction

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. According to the Renewable Fuels Association[1], world fuel ethanol production reached approximately 25.7 millions gallons in 2015 compared to 13.1 millions gallons in 2007, that is to say a nearly doubling of production in 8 years. The U.S. and Brazil account for more than 85% of the world production followed by Europe (5.5%) and China (3%) (Figure 1). The U.S. is the largest ethanol producer in the world and represents more than 57% of the world production and according to the Energy Information Administration[2], fuel ethanol accounted for 10% of the U.S. gasoline blend. The main feedstock for ethanol production in the U.S. is corn (at 90%) which can explain the localisation of ethanol plants in the Midwest, the dominant region for corn production (Corn Belt). The ethanol inclusion policy in U.S. gasoline blends, the relative price between ethanol and corn grains in the international market as well as the fiscal incentives (tax exemption) are the key determinants of the evolution of the market.

Figure 1: Global Ethanol Production by Country/Region and Year

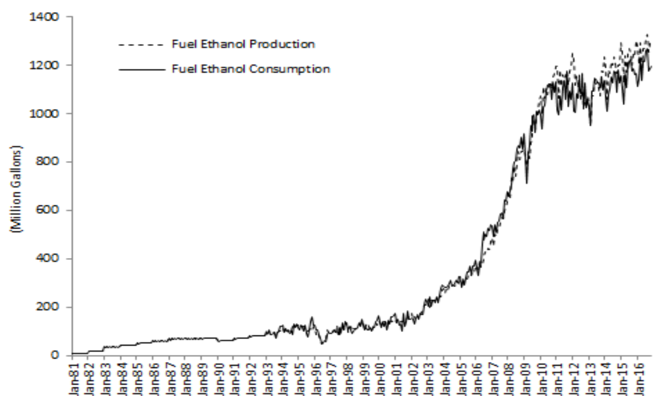


[1]Renewable Fuels Association. http://www.ethanolrfa.org/resources/industry/statistics/1454098996479-8715d404-e546

[2]https://www.eia.gov/energyexplained/?page=biofuel_ethanol_home

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 2).

Figure 2: Monthly U.S. ethanol production and consumption



Source: U.S. Energy Information Administration

First consumer of energy in Latin America (7th largest consumer in the world), Brazil holds the second Oil reserves of South America, with nearly 13 billion barrels, far behind Venezuela. Since the 1970s, Brazil has been a net oil importer and the different government has put in place two main types of measures to ensure the country's oil independence. The first one leads to the development of the oil potential of the country by investment in exploration and production through its national oil company (NOC) Petrobras. The second one was based on ethanol. In 1975 just after the first oil shock of 1973-1974, the Brazilian government launched its first biofuel production program (called Pro-alcohol Program), which based on the conversion of sugarcane into bioethanol in order to reduce its imports of gasoline. Various tax measures were introduced during this period (production subsidy, fiscal incentives or money rebates for the purchase of specific vehicles, etc.) and were strengthened in the late 1970s, after the second oil shock until the early 1980's. Nowadays

Brazil accounts for 28% of world production but contrary to the U.S. where ethanol production sharply increased by 127% between 2007 and 2015, Brazilian ethanol production increased by only 40% during the same period of time leading to an important loss of market share in the world ethanol market. 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[3] 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 2007 (Figure 3) and the range of prices has extended from 1.47 USD per gallon to more than 4.00 USD per gallon following the volatility observed during this period of time in the energy and agricultural prices.

Figure 3: U.S. Ethanol spot prices

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

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 which contribute to increase the liquidity within the market. In 2007 options contracts were also launch on the market. In Brazil the Brazilian Mercantile and Futures Exchange (BMF)launched its first sugar-based ethanol contract in 2000 but the sharp volatility of the USD-real exchange rate and the lack of liquidity in 2007 triggered major changes in term of contracts specifications. On the CBOT the volume 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.

Our main assumption relates to the fact that futures market can help in understanding the ethanol price dynamic during the period of instability and that it can exacerbate the dynamic observed in the ethanol market during tension periods whereas it won't appear as a determinant factor during ≪normal≫ or bearish period. This assumption leads us to adopt a specific econometric methodology based on non-linear models, a Markov chain model which allows for changes in the short run and volatility dynamic. We estimate a Markov Switching Vectorial Error Correction model (MS-VECM) including a multivariate Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) error structure. This specification allows the coefficients, both in the short-run and volatility processes, to switch between two distinct states (standard state and crisis state). Hamilton (1989) proposes the Markov Switching models while Krolzig (1999) extends this specification for vector autoregressive model. The main contributions of this work are fourfold. First, we are able to analyse both market efficiency and dynamic hedge ratio concerning the ethanol market for the first time. Second, we include adjustment to long-term equilibrium and regimes shifts, as Alizadeh et al. (2008), asymmetric behaviour of variance process, as Brooks et al. (2002), as well as regime switching short-run dynamic between spot and futures prices, as Salvador and Arago (2014) to estimate optimal hedge ratio. Third, we propose to use the nonparametric cointegration approach from Nielsen (2010) to eliminate estimation bias on the long-run dynamic. Fourth, we will able to discriminate between the different hedge ratios estimated from different specifications in terms of variance reduction and utility rise using in-sample and out-of-sample tests.

In the first section, we present the literature review. In the second section, we present data and the Markov Switching Vector Error Correction model (MS-VECM). The third section presents empirical results. 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.

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.[4] 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 with a non-unit coefficient between spot and futures prices.

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. 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

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

asset prices. They propose to estimate 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, 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, 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 improvements for most of the markets studied. Dark (2015) confirms Alizadeh et al. (2008)'s results and improves effectiveness of the hedge ratio by adding long memory to the variance process. Finally, Brooks et al. (2002) show the improvements of the hedge ratio effectiveness with the integration of the volatility asymmetric response against positive and negative shocks, i.e. the leveraged effect. 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.

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. 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 series in their first-difference. In addition, the Ljung-Box (1978) test's confirms the presence of autocorrelation. 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.

We apply the Johansen (1988) test's to check the existence of a long-term relationship with unit cointegrating vector and estimate the conditional mean with a Markov regime 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 estimate 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 nonlinear 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 estimated with this model outperforms standard hedge ratios in many energy markets (Alizadeh et al., 2008).

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	0.209	0.020	0.017
Skewness	-0.010	0.135	-0.393	-0.660
Kurtosis	1.831	1.625	11.591	7.331
ADF	0.047*	0.306	0.001*	0.001*
PP	0.099	0.300	0.001*	0.001*
KPSS	0.010	0.001	0.100*	0.100*
Q(6)	0.001	0.001	0.001	0.012
$Q^2(6)$	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) test (PP) and Kwiatkowski *et al.* (1992) test (KPSS). The star mentions the stationarity of the variable. Q(6) and $Q^2(6)$ are the p-value of the Ljung-Box (1978) test and ARCH test (Engle, 1982) for 6^{th} order autocorrelation.

However, the Johansen (1988)'s cointegration tests requires assumptions regarding the short-run dynamic which is a linear process. By using Johansen'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.[5] In addition, the estimated cointegration coefficients are provided by the cointegration testing procedure and converges to their real value. Therefore, by using both Johansen (1988) and Nielsen (2010) cointegration approach, we can analyze the effect of the long-term estimation bias on the hedge ratio efficiency.

The MS-VECM with GARCH error structure can be expressed by

$$\begin{aligned} \Delta X_t &= \sum_{i=1}^{p-1} \Gamma_{i,st} \Delta X_{t-1} + \Pi_{st} X_{t-1} + \epsilon_{t,st} \\ \epsilon_{t,st} &= \begin{pmatrix} \epsilon_{s,t,st} \\ \epsilon_{f,t,st} \end{pmatrix} |\Omega_{t-1} \backsim IN(0, H_{t,st}) \end{aligned} \tag{6}$$

where $\Delta X_t = (\Delta s_t, \Delta f_t)'$ (resp. $X_{t-1} = (s_{t-1}, f_{t-1})'$) is the vector of returns (resp. log-price). $\Gamma_{i,st}$ et Π_{st} are coefficient matrices related on short- and long-term adjustments to X_t variations, 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 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 to check the existence of unitary long-term coefficients between spot and futures prices (Johansen, 1995). The non reject of the null hypothesis of unit coefficient will approve the Garbade and Silber (1983) model against that proposed by Figuerola-Ferretti and Gonzalo

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

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

(2010). Finally, we apply the Nielsen (2010)'s nonparametric cointegration analysis to test the cointegration relationship existence and to estimate cointegration coefficients.

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,

$$\hat{P} = \begin{pmatrix} P_{11} & P_{21} \\ P_{12} & P_{22} \end{pmatrix} = \begin{pmatrix} 1 - P_{12} & P_{21} \\ P_{12} & 1 - P_{21} \end{pmatrix} \tag{7}$$

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). So, 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

$$H_{t,st} = C'_{st}C_{st} + A'_{st}\epsilon_{t-1}\epsilon'_{t-1}A_{st} + B'_{st}H_{t-1}B_{st} + D'_{st}\eta_{t-1}\eta'_{t-1}D_{st} \tag{8}$$

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 pas shocks, i.e. $\eta_t = min(\epsilon_t, 0)$. 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 past negative shock effects, 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 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

$$h_{ss,t} = \pi_{1,t}(r^2_{s,1,t} + h_{ss,1,t}) + (1 - \pi_{1,t})(r^2_{s,2,t} + h_{ss,2,t}) - [\pi_{1,t}r_{s,1,t} + (1 - \pi_{1,t})r_{s,2,t}]^2 \tag{9}$$

$$h_{ff,t} = \pi_{1,t}(r^2_{f,1,t} + h_{ff,1,t}) + (1 - \pi_{1,t})(r^2_{f,2,t} + h_{ff,2,t}) - [\pi_{1,t}r_{f,1,t} + (1 - \pi_{1,t})r_{f,2,t}]^2 \tag{10}$$

$$\begin{aligned} h_{sf,t} = {} & \pi_{1,t}[r_{s,1,t}r_{f,1,t} + h_{sf,1,t}] + (1 - \pi_{1,t})[r_{s,2,t}r_{f,2,t} + h_{sf,2,t}] \\ & -[\pi_{1,t}r_{s,1,t} + (1 - \pi_{1,t})r_{s,2,t}][\pi_{1,t}r_{f,1,t} + (1 - \pi_{1,t})r_{f,2,t}] \end{aligned} \tag{11}$$

In equations 9, 10 and 11, $\pi_{st,t}$ 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.

$$\epsilon_{s,t} = \Delta s_t - [\pi_{1,t} r_{s,1,t} + (1 - \pi_{1,t}) r_{s,2,t}] \tag{12}$$

$$\epsilon_{f,t} = \Delta f_t - [\pi_{1,t} r_{f,1,t} + (1 - \pi_{1,t}) r_{f,2,t}] \tag{13}$$

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:

$$\begin{aligned} f(X_t, \theta) = & \frac{\pi_{1,t}}{2\pi} |H_{t,1}|^{-\frac{1}{2}} exp(-\frac{1}{2} \epsilon'_{t,1} H_{t,1}^{-1} \epsilon_{t,1}) \\ & + \frac{\pi_{2,t}}{2\pi} |H_{t,2}|^{-\frac{1}{2}} exp(-\frac{1}{2} \epsilon'_{t,2} H_{t,2}^{-1} \epsilon_{t,2}) \end{aligned} \tag{14}$$

$$L(\theta) = \sum_{t=1}^{T} log f(X_t, \theta) \tag{15}$$

The log-likelihood function, expressed in the equation 15, 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 estimate the dynamic hedge ratio as

$$\delta_t | \Omega_{t-1} = \frac{h_{sf,t-1}}{h_{ff,t-1}} \tag{16}$$

where $h_{sf,t-1}$ et $h_{ff,t-1}$ are defined in the equations (11) et (10).

4 Empirical results

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 apply 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's (1983) theory is valid to explain the long-term link between spot and futures prices on the ethanol market. Finally, the causality tests conclude on a price discovery process from futures to spot prices, at a 10% significant level.

Table 2: Cointegration and causality test

$$\beta_S S_t + F_t + \beta_0 = u_t$$

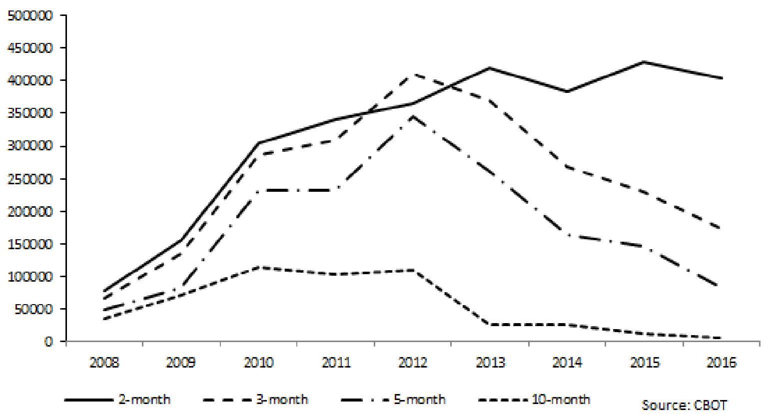
Lags	H_0	P-value		Cointegration vector	LR test	
		$\lambda_{max} test$	$\lambda_{trace} test$	(β_S 1 β_0)	$H_0 : \beta_S = -1$	$H_0 : \beta_0 = 0$
1	r=0	0.001	0.001	(-1.044 1 0.109)	0.078	0.001
-	H_0	Test stat	Critical Value	Cointegration vector	-	-
-	r=0	3.78	3.57	(-1.011 1 -)	-	-

Causality test	Pvalue
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 choosen 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 tests refer to the Toda and Yamamoto (1995) test which null hypothesis is the absence of long-term causality.

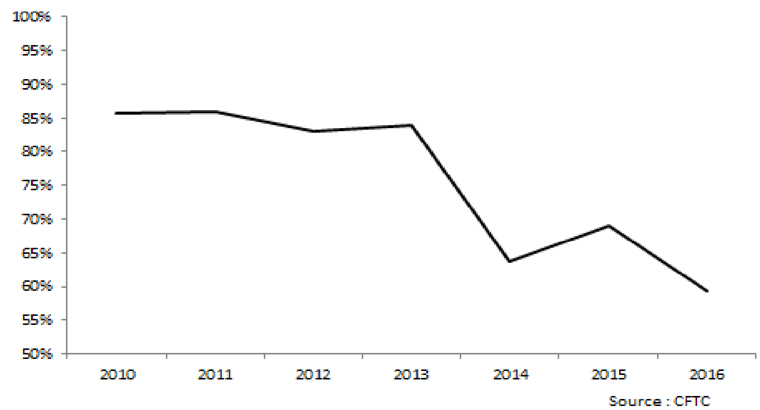
During the previous decades and especially in the initial phase of construction of the ethanol futures market, the main objective was to attract and concentrate the liquidity required for commercial traders to achieve hedging activities. Nevertheless, the rise in transaction volumes has been accompanied 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, 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 4: Open interest by contracts maturity



On the 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 Chicago Board of Trade), these transactions have risen, for two-month term contracts, from around 78864 in 2008 to 404133 in 2016, i.e. multiplied by a factor of 5 (Figure 4). On the other hand, the share of non-commercial players increased from around 15% before 2008, to over 35% on average since 2014 (Figure 5). 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. 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 (Hache and Lantz, 2013; Medlock and Jaffe, 2009).

Figure 5: Commercial positions



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.

Table 3: Long-term coefficient for sub-sample

	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016
$\lvert\beta_S\rvert$	1.023	0.919	0.990	0.860	3.738	1.708	0.766	0.298
Test	0.191	0.071	0.803	0.001	0.001	0.002	0.007	0.003

Note: The first line mentions the long-term coefficient for a two-year estimation with the Johanson (1988)'s procedure. The second line mentions the p-value for the unity constraint test, c.f. note table 2.

The decrease in transaction volume on the ethanol market for maturity contracts greater than 2 months could be explained by the results presented in Table 3. Indeed, the unit relationship between spot and futures prices is rejected at a 5% significant level for all two-year periods since 2011. In addition, situations of long-run backwardation, $|\beta_S| < 1$, and contango, $|\beta_S| > 1$, alternate. Its changes of the market conditions could lead to the exit of many agents (Figure 6), especially commercial agents, from the market due to difficulties of making expectations.

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.

Figure 6: Position (number of contracts) by actors

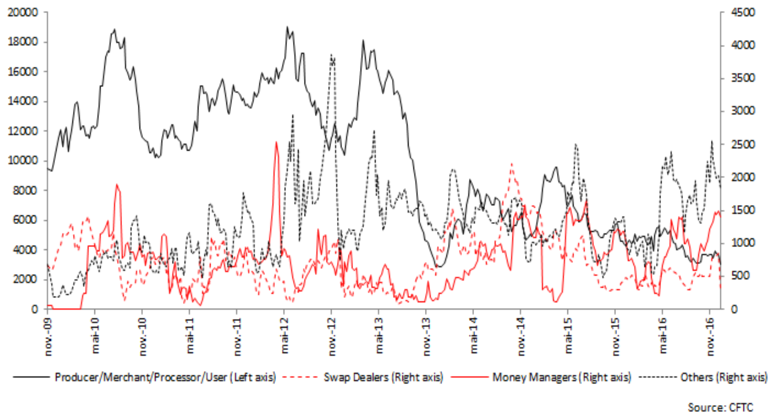


Table 4 presents results for both linear and nonlinear models.[7] As expected, linear model presents several non significant coefficients due to the existence of regime shifts. The two coefficients measuring the speed of adjustment to the long-run equilibrium, α_i, are significant and negative. In addition, the higher coefficient for spot prices highlights its faster adjustment to the long-term equilibrium compared to futures prices. This result is in line with the price discovery role of futures markets. The nonlinear specification provides more information concerning the relations between spot and futures prices of ethanol with many significant coefficients and all residual diagnostics confirm that the nonlinear model is well specified.

Concerning the nonlinear model results, all adjustment coefficients are negative and significant. In each states, the spot prices adjust to equilibrium more than futures prices, highlighting the role of futures markets in the price discovery process. Note that this adjustment process is faster during high volatility regime, $st = 1$, compare to low volatility state, $st = 2$, confirming our expectation that futures market can help in understanding the ethanol price dynamic during the period of instability. Furthermore, this result highlights that the dynamic between the ethanol spot and futures prices is regime dependant confirming the ability of our Markov Switching specification to describe it. Finally, the higher adjustment coefficients during high volatility regime lead to high price changes to adjust to long-term equilibrium which could lead to a more volatile market.

Turning to the conditional variance equation, the variance process is non-stationary in the high volatility state with $a_{ii}^2 + b_{ii}^2 > 1$. However, this problem is resolved with the inclusion of asymmetric responses for conditional variance to past shocks. As expected, the variance persistence is lower during low volatility regime compare to

[7]We present results for the best model, i.e. without asymmetry. Other results are available upon request. In addition, results concern model only with the Johansen (1988)'s cointegration estimation in this draft.

high volatility state as well as linear specification.

Finally, the probability to switch from high to low variance states is greater compare to the probability to switch from low to high variance regimes. This result indicates a shorter duration for high volatility regimes and is confirmed by the average expected state duration calculation proposed by Hamilton (1989).[8] These durations are 1.19 and 3.48 weeks for high and low volatility regimes, respectively.

Figure 7 presents the "smooth" probability of being in the high variance regime.[9] This regime is mainly apparent during the beginning of our sample, i.e. 2008-2009, 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 4 and 6).

[8] The average expected duration of state i can be calculated by $(P_{ij})^{-1}$.

[9] The "smooth" probability is the estimated probability of being in regime i given information of the entire sample. See Hamilton (1994) for further details on its calculation as well as on others probabilities existing.

Table 4: Estimation results

$$S_t = \beta_F F_t + \beta_0 + u_t$$

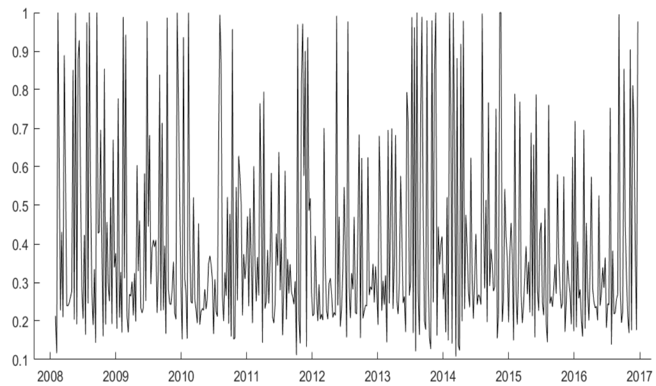
$$\begin{pmatrix}\Delta S_t\\ \Delta F_t\end{pmatrix} = \begin{pmatrix}\alpha_S\\ \alpha_F\end{pmatrix} u_{t-1} + \begin{pmatrix}\gamma_{SS} & \gamma_{SF}\\ \gamma_{FS} & \gamma_{FF}\end{pmatrix}\begin{pmatrix}\Delta S_{t-1}\\ \Delta F_{t-1}\end{pmatrix} + \begin{pmatrix}\epsilon_{S,t}\\ \epsilon_{F,t}\end{pmatrix} \qquad \begin{pmatrix}\epsilon_{S,t}\\ \epsilon_{F,t}\end{pmatrix}|\Omega_{t-1} \backsim N(0,H_t)$$

$$H_t = \begin{pmatrix}c_{11} & c_{12}\\ 0 & c_{22}\end{pmatrix}'\begin{pmatrix}c_{11} & c_{12}\\ 0 & c_{22}\end{pmatrix} + \begin{pmatrix}a_{11} & 0\\ 0 & a_{22}\end{pmatrix}'\begin{pmatrix}\epsilon_{S,t-1}\\ \epsilon_{F,t-1}\end{pmatrix}\begin{pmatrix}\epsilon_{S,t-1}\\ \epsilon_{F,t-1}\end{pmatrix}'\begin{pmatrix}a_{11} & 0\\ 0 & a_{22}\end{pmatrix} + \begin{pmatrix}b_{11} & 0\\ 0 & b_{22}\end{pmatrix}' H_{t-1}\begin{pmatrix}b_{11} & 0\\ 0 & b_{22}\end{pmatrix}$$

	VECM-GARCH		MS-VECM-GARCH			
	$\hat{\beta}$	(P-value)	$\hat{\beta}_{st=1}$	(P-value)	$\hat{\beta}_{st=2}$	(P-value)
Mean equation						
β_S	1		1			
β_F	0.958		0.958			
β_0	0.105		0.105			
α_S	-0.130	(0.001)	-0.363	(0.001)	-0.070	(0.001)
α_F	-0.049	(0.016)	-0.126	(0.001)	-0.000	(0.001)
γ_{SS}	-0.101	(0.178)	-0.344	(0.001)	-0.058	(0.001)
γ_{SF}	0.245	(0.009)	0.412	(0.001)	0.236	(0.001)
γ_{FS}	0.090	(0.279)	-0.152	(0.001)	0.108	(0.001)
γ_{FF}	-0.073	(0.397)	-0.015	(0.001)	-0.043	(0.001)
Variance equation						
c_{11}	-0.019	(0.010)	-0.016	(0.001)	-0.024	(0.001)
c_{12}	-0.012	(0.018)	-0.004	(0.001)	-0.020	(0.001)
c_{22}	0.000	(0.999)	-0.009	(0.001)	0.005	(0.001)
a_{11}	-0.528	(0.001)	-0.795	(0.001)	-0.383	(0.001)
a_{22}	-0.350	(0.001)	-0.348	(0.001)	-0.311	(0.001)
b_{11}	0.774	(0.001)	-1.016	(0.001)	-0.453	(0.001)
b_{22}	0.898	(0.001)	-1.18	(0.001)	-0.531	(0.001)
Transition prob.						
P_{12}	-	(-)	0.838	(-)		
P_{21}	-	(-)	0.287	(-)		
Res. diagnostics	S	F	S		F	
JB	0.001	0.001	0.226		0.270	
Q(6)	0.777	0.865	0.267		0.693	
$Q^2(6)$	0.139	0.905	0.546		0.687	

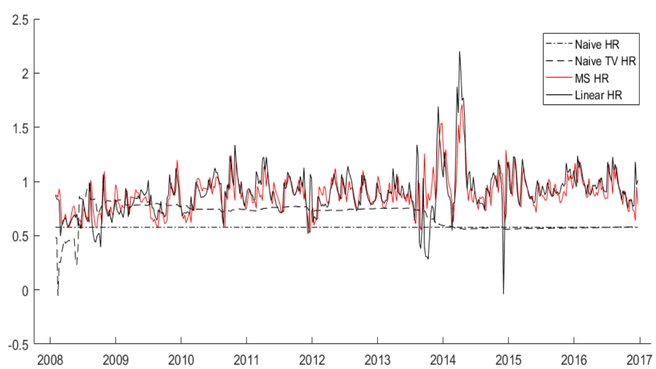
Note: For each model or state, the first column is the estimated coefficients while the second refers to the p-value of the Student test. The coefficient is significant at the 10%, 5% or 1% if p-value is less than 0.10, 0.05 or 0.01, respectively. JB, Q(6) and $Q^2(6)$ are the Bera and Jarque (1980) test for normality, the Ljung-Box (1978) test and the ARCH test (Engle, 1982), respectively.

Figure 7: Smooth probabilities of being high volatility state



Our linear and Markov Swithching representations of the ethanol market allow us to estimate the dynamic hedge ratios presented in Figure 8. We mention also the "naive" and "naive time-varying" hedge ratios of Ederington (1979) and Kroner and Sultan (1993), respectively. We can note that this two "naive" models seem to be underestimated. In addition, we provide in Figure 9 the hedge ratios estimating from our linear and Markov Switching models with asymmetry as well as cross-hedge ratios with gasoline markets, with all models previously mentioned, in Figures 10 and 11. These latter will allow us to compare direct hedging with the ethanol futures market and cross-hedging with the gasoline futures market.[10] This market was usually used to risk hedging before the ethanol futures market beginning (Dahlgran, 2009).

Figure 8: Constant and dynamic hedge ratios



[10]New York Harbor Reformulated RBOB Regular Gasoline.

Figure 9: Constant and dynamic hedge ratios with asymmetric model

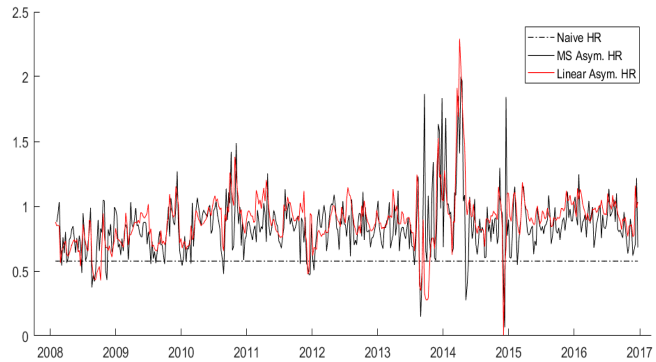


Figure 10: Constant and dynamic cross-hedge ratios

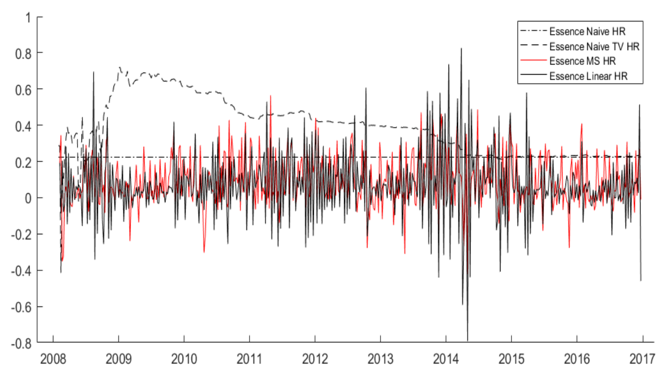
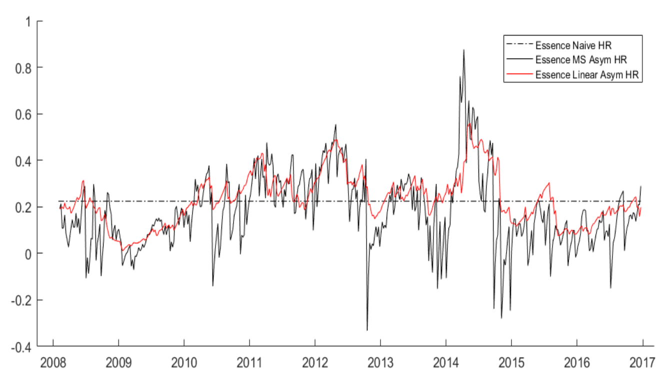


Figure 11: Constant and dynamic cross-hedge ratios with asymmetric model



5 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 and out-of-sample analysis. For this purpose, we use a Markov Regime Switching Vector Error Correction Model with GARCH error structure. This specification allows us to study the long-term, short-term and variance dynamics across different volatility regimes.

Our results are four-fold. First, the long-term equilibrium in the ethanol market is well explained by the Garbade and Silber (1983) theory about efficiency in storable commodity markets, compare to the Figuerola-Ferretti and Gonzalo (2010) model, with a price discovery process from futures to spot prices. Second, this result is only valid during the 2008-2011 period. Since 2011, the ethanol market alternates between long-term backwardation and contango. Third, a difference exist between long-term estimation depending on the long-term estimation procedure. Fourth, our different specifications allow us to estimate a large variety of dynamic hedge ratios. We will perform a hedging effectiveness analysis in terms of variance reduction, increase in utility and reduction in the value-at-risk.

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