**Do RIN Mandates and Blender's Tax Credit Affect Blenders' Hedging Strategies?**

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*ABSTRACT*

*In this study stylized gasoline blender's optimal hedging strategy in the presence of ethanol mandates is analyzed. In particular, the main objective of this study is to investigate whether the ability to purchase RINs and the presence of tax incentives would affect blenders' optimal hedging strategies. Multicommodity hedging method with Lower Partial Moments hedging criterion as a measure of downside risk is utilized in obtaining the optimal hedge ratios. Based on the obtained results, the Renewable Identification Number purchases do not reduce risk, hence, is not a good risk management tool in the presence of blenders' tax credits. However, in the absence of tax credit, RINs can be used as a risk management tool.*

Keywords: Ethanol, RINs, hedging, LPM

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## Introduction

Oftentimes businesses want some degree of stability in their cash inflows or outflows in order to establish reliable financial planning and meet company's financial obligations and commitments. Typically most businesses, whether it is an ethanol producer, a farmer, or a financial institution, are exposed to some degree of price risk on assets used or produced in their business activities. Therefore, businesses or individual investors use hedging as a risk management tool to reduce the risk of adverse price changes by taking positions in the futures or options markets.

Traditionally, gasoline blenders used Methyl Tertiary Butyl Ether (MTBE) as a gasoline oxygenate to produce blended gasoline. By the end of 1990s, several states started banning MTBE after discovering its negative effects on health and environment as result of gasoline leakage incidents. In 2000, Environmental Protection Agency (EPA) recommended that the use of MTBE should be banned across all the states. By 2004, 18 states banned the use of MTBE and started switching to ethanol as a gasoline oxygenate.

Several laws related to health and environmental protection, energy independence, and resulting economic incentives have accelerated the adoption of biofuels in the United States. Energy Policy Act of 2005 (EPAct) established the renewable fuel volume mandate by requiring that 7.5 billion gallons of national fuel supply be provided by renewable fuels by 2012. The Energy Independence and Security Act of 2007 (EISA) further expanded the EPAct by requiring 36 billion gallons of renewable fuels blended into gasoline and diesel by 2022. Epact and EISA stipulates Renewable Fuel Standards (RFS1 and RFS2 respectively) and authorizes the EPA to facilitate the RFS mandates.

In addition, these biofuels related policies provide various incentives to biofuels producers and blenders. For instance, an ethanol blender, who is registered with Internal Revenue Service (IRS), is eligible for a Volumetric Ethanol Excise Tax Credit (VEETC) incentive in the amount of 45 cent per gallon of pure ethanol blended with gasoline. VEETC expires on December 31, 2011.

Renewable Identification Numbers (RINs) are developed as a tracking mechanism in order to implement the compliance with RFS mandates (Thompson et al 2010). EPA issues RINs for every batch of produced or imported biofuels that is in compliance with mandate guidelines. EPA requires fuel blenders submit specified amounts of RINs as a proof that they are blending biofuels into conventional fuels. The RINs can be obtained by purchasing biofuels from the producers. If blenders purchase more biofuels than their mandated amount, they can sell the extra RINs to other blenders to meet their mandates. Depending on the RIN prices (per RIN-gallon), the blenders have the flexibility either to purchase the biofuels (which comes with RINs) from the producers or to purchase RINs from other blenders.

In this study stylized gasoline blender's optimal hedging strategy in the presence of ethanol mandates is analyzed. In particular, the main objective of this study is to investigate whether the ability to purchase RINs and the presence of tax incentives would affect blenders' optimal hedging strategies.

**Review of Hedging Literature**

There are very few studies have been done related to hedging in multi-commodity setting, most of which utilize traditional minimum-variance (MV) and mean-variance criteria that assume normality. Lower partial moments (LPM) criterion combined with copula approach is an alternative to the traditional criteria and presents a great potential in multi-commodity hedging. LPM criterion looks at risk from downside perspective and copulas are flexible enough to accommodate parametric and nonparametric distributions.

MV criterion is the most commonly used approach in determining the optimal hedge ratio (e.g. Hull, 2003, p. 79). For instance, Ederington (1979) used MV criterion and proposed hedge effective-ness measure, $r^2$, to evaluate Government National Mortgage Association (GNMA), Treasury Bill (T-Bill), corn, and wheat futures markets. One of their main findings is that the optimal hedge ratio was less than one in most cases, hence, optimal hedging strategy is not an equal and opposite hedge. Benninga, Eldor, and Zilcha (1983) examine MV hedge ratios in futures markets under two assumptions: 1) futures prices are unbiased and 2) basis between futures and spot prices is independent of spot price. They conclude that, under above assumptions, MV optimal hedge ratios are independent of preferences. However, later studies by other authors show the short-comings of this approach. Lence (1995) argues that MV approach relies on set unrealistic assumptions. For instance, it ignores transaction costs, borrowing and lending, and alternative investment activities. He concludes that MV hedge maximizes expected utility under restrictive assumptions, but results in sub-optimal hedging strategies when those assumptions are relaxed.

Meyer (1987) showed that when the return distributions are elliptically symmetric then the two-moment decision model $V(\sigma,\mu)$ is consistent with expected utility maximization. Furthermore, he showed that when $\partial S(t\sigma,t\mu)/\partial t=0$, where $S(t\sigma,t\mu)=-V_{\sigma}(\sigma,\mu)/V_{\mu}(\sigma,\mu)$ (prop. 6) holds $V(\sigma,\mu)$ exhibits constant relative risk aversion (CRRA). By using these conditions, Nelson and Escalante (2004) showed that $E\big(U(W_1)\big)=V(\sigma,\mu)=-(\mu^2-\gamma\sigma^2)^{-1}$ is a concave function in $(\sigma,\mu)$ space and exhibits general CRRA preferences. They applied this mean-variance objective function to an optimal leverage, farm finance, and optimal broiler contract models. They found that this objective function provides better analytical solutions than that of linear mean-variance model.

The hedgers are more concerned about their losses (downside risk) than extraordinary profits (upside potential) and therefore view risk as being downside deviations from the mean. Many studies (e.g. Unser, 2000) confirm this notion of downside risk. Thus, this implies that the appropriate way of minimizing risk is minimizing downside risk. Traditional risk minimization criteria, MV and mean-variance, can be used to minimize downside risk given the elliptical distributional assumptions underlying these criteria are met. However, recent studies challenged the validity of this assumption and many empirical studies confirmed that asset returns are not normal or elliptical in general. When the normality assumption is violated, the use of MV and mean-variance criteria leads to overhedging since upside potential is also considered as risk in the traditional hedging.

An alternative approach, lower partial moments (LPM), was proposed by Fishburn (1977). This criterion accommodates any distributional assumptions and defines risk as shortfalls from a specific target return. Bawa (1978) established the relationship between the expected utility maximization method and the lower partial moment minimization method and showed that an *n*th order lower partial moment is compatible with stochastic dominance of order $n + 1$. Lien and Tse (2000) applied lower partial moments of order one to three with different levels of target returns to analyze the behavior of optimal hedge ratios and compared them with MV based hedge ratios. The optimal hedge ratios were estimated by the empirical distribution function method and the kernel density estimation method. The study used data on spot and futures prices of Nikkei Stock Average (Nikkei 225) index which consists of daily observations from January

1988 to August 1996. They found that LPM based strategies significantly differ from MV based strategies and if a hedger is concerned about downside-only risk, then MV hedge is inappropriate.

Both Tzang & Leuthold (1990) and Fackler & McNew (1993) analysed optimal hedge ratios for soybean processors under mean-variance criterion in multi-commodity setting. Even though each study recommended somewhat different specific optimal hedge ratios, both obtained similar findings. They found that multiproduct hedging strategies provide significant risk reductions relative to optimal hedging strategies based on single commodity. However, Collins (2000) challenged the validity of these claims in his study of U.S. soy complex. He argues that neither multivariate hedging models nor the univariate counterpart better risk management over a simple equal and opposite hedging strategy. Power and Vedenov (2010) studied the LPM based hedging strategies in multi-commodity setting. They used the data determined kernel copula approach to model the joint distribution of cash and futures prices of underlying commodities. Optimal hedge ratios are estimated for representative Texas feedlot operation based on actual cash and future prices of corn and live cattle. Their results confirmed the findings of earlier studies where LPM based optimal hedge ratios are significantly lower than that of minimum-variance criterion. However, the results show that an optimal strategy for corn was a speculative position, which is somewhat unexpected.

When returns on the underlying assets are non-normal then the linear correlation is not a useful indicator of dependence and the use of copula functions resolves this problem. Copulas can model dependence structure in both elliptical and non-elliptical distributions. Copula functions tackle the specification of marginal distributions and modeling the dependence structure separately (e.g. Cherubini and Luciano, 2003; Dowd, 2005; Fischer *et al.,* 2009). Thus, copulas offer more flexibility, where we can first fit appropriate marginal distributions to each underlying risk variable and then fit appropriate dependence structure. In other words, copula functions break the construction of joint distributions into two separate parts: the choice of marginal distribution functions and the choice of copula function, thus allowing dependence structure to be modeled independently of the marginal distributions of random variables (Martellini and Meyfredi 2008).

Fischer *et al.* (2009) compared the different copula models including Clayton and Gumbel copulas from Archimedean class, two hierarchical copula models from the generalized Archimedean copula family, Gaussian copula, and the Student-t copula. The Student-t copula is used as a benchmark. All models are estimated by maximum likelihood method. The data set used is returns on four assets from each of the German stock market (DAX), foreign exchange markets, and London Metal Exchange (LME). Their findings indicate that Student-t copula gives the best fit over all measures. Rotated Gumbel copulas outperform other approaches within the class of pair-copulas itself. Archimedean copulas outperform in the bivariate case, whereas Gaussian copula in higher dimensions with the latter having the best overall goodness-of-fit measure.

**Hedging Problem**

We assume that an independently owned gasoline terminal facility, which is not involved in refining process, is exposed to risk in the output and input markets. It purchases Reformulated Gasoline Blendstock for Oxygen Blending (RBOB) from the refinery and only blends and stores gasoline which is then transported to retail gas stations. We also assume that a gasoline blender hedges his non-tradable spot position of blended gasoline $Q^B$ in the output market, $kQ^B$ of unblended gasoline (RBOB) and $(1-k)Q^B$ of pure ethanol in the input markets at the beginning of the period, t=0.

The blender wants to minimize his risk by purchasing futures contracts for $kQ^B$ units of RBOB and $(1-k)Q^B$ units of pure ethanol, hence becoming a short hedger, at $t=0$ in the futures market. Let $p_0$ and $p_1$, denote spot prices at the beginning and at the end of hedging period respectively. Alternatively, $f_0$ and $f_1$ are the futures prices at time 0 and 1 respectively. Then, blender's end-of period profit can be written as follows:

$$\pi(h) = P^B - P^G * kQ_1^B + (0.45 - P^E) * (1 - k + 0.043) * Q_1^B - P^{RIN} * (k - 0.9) * Q_1^B$$
$$+h_1^G * (f_1^G - f_0^G) * kQ_1^B + h_1^E * (f_1^E - f_0^E) * (1 - k + 0.043) * Q_1^B$$
$$0.9 \leq k \leq 0.957 \qquad (1)$$

where $P^B, P^G, P^E, and\ P^{RIN}$ are the spot prices of blended gasoline, RBOB gasoline, pure ethanol, and RIN respectively at the end of a hedging period. *k* is the ratio of RBOB to blended gasoline and the rest comes from an ethanol blending. The coefficient 0.45 represents the blenders' tax credit per unit of pure ethanol blended. The coefficient 0.043 corresponds to the minimum volume of oxygenate concentration required by EPA. For ethanol this requirement amounts to 4.3% in the total volume of blended reformulated gasoline if the blenders use averaged basis. Thus, blenders must use ethanol as an oxygenate, or alternative additive, in tha amount of 4.3% of total blended volume. The government does not mandate more than 10% ethanol blending and therefore *k* varies between 0.9 and 0.957, but it can be more on voluntary basis. Since the blenders' have the option to fulfill their mandates by purchasing RINs instead of blending the physical product, $(k-0.9)Q_1^B$ is the amount of ethanol mandate that can be met with RIN purchase. Here, we are making an implicit assumption that other non-banned substitute oxygenate products' costs or the amount per blended gasoline are small enough not to account for this alternative scenario. If not, the profit function needs to be properly modified.

**Minimum LPM hedge ratio**

As it was mentioned earlier, the LPM is a measure of downside risk and is compatible with stochastic dominance principle. The *n*th-order lower partial moment ($LPM_n$) of a random variable $r$ with a target return $\bar{r}$ is defined as follows:

$$LPM_n = \int_{-\infty}^{\bar{r}} (\bar{r} - r)^n dF(r) \qquad (2)$$

where $F(r)$ is the multivariate distribution function of a random return r. The return greater than $\bar{r}$ is desirable and anything lower considered as risk. Therefore, hedger tries to minimize any return below the target level and the $h*$ attains the optimal hedge ratio when LPM function reaches the minimum.

The joint distribution is constructed by copulas and they enable us to create multivariate joint distribution from univariate distributions. When modeling the joint distribution with copula, we first specify the marginal distributions, then choose the appropriate type of copula and estimate its parameters, and then we apply the copula function to marginals to get the joint distribution. Then, we can use that constructed joint distribution with desired hedging criterion to obtain the optimal hedge ratio.

## Empirical model and methodology

$Q_1^B$ can be omitted from blender's profit function since it serves as a scalar.

$$\pi(h) = P^B - P^G * k + (0.45 - P^E) * (1 - k + 0.043) - P^{RIN} * (k - 0.9)$$
$$+h_1^G * (f_1^G - f_0^G) * k + h_1^E * (f_1^E - f_0^E) * (1 - k + 0.043)$$
$$0.9 \leq k \leq 0.957 \tag{3}$$

Lower partial moment of order 2, $LPM_2$, will be used in the analysis. Blender's objective is to minimize any shortfalls below the target profit. Thus, we have the following minimization problem for a blender to obtain the optimal hedge ratio:

$$LPM_2 = \int_{-\infty}^{\bar{\pi}} \left(\bar{\pi} - \pi(h)\right)^2 dF\left(\pi(h)\right) \tag{4}$$

where π is blender's profit function as defined earlier, $\bar{\pi}$ is the expected profit without hedging, $dF(\pi)$ is the multivariate distribution of π, and $\boldsymbol{h} = [h^G, h^E, k]$ is a vector of hedge ratios.

Before estimating the optimal hedge ratios using LPM criterion, the joint distribution of five price series needs to be constructed. Gaussian copula is chosen to model the joint distribution. First, empirical distributions of log-differenced values of price series are obtained and the dependence structure is modeled with Gaussian copula. Then ten thousand simulated log-differenced series are generated using Gaussian copula and inverse empirical marginals. In order to accommodate the presence of a blenders' tax credit, since it does not vary overtime, the simulated series are converted to levels by using sample average prices.

Blenders' tax credit, though expired in the end of 2011, and possibility of RIN purchases are considered separately and together in three scenarios.

## Data

The price series for the analysis are obtained via datastream. New York Harbor oxygenated and non-oxygenated (RBOB) spot prices are used for blended ($P^B$) and unblended ($P^G$) gasoline prices respectively. For gasoline futures prices, nearby RBOB futures contract from NYMEX are used. Ethanol spot prices are for New York harbor and futures prices come from CBOT nearby ethanol futures contracts. RIN prices are obtained from HARTENERGY's weekly Ethanol & Biofuels News and are based on survey of ethanol blenders. All the price series are daily prices and starting from June 23, 2006 to March 17, 2012 and sampled weekly to match the weekly RIN prices. The weekly RIN prices start from May 14, 2010 and end on March 17, 2012 that corresponds to 93 weekly observations. The dataset includes 1543 observations of five daily price series that resulted in 292 weekly series. Four-week rolling window is used in the analysis.

The price series do not exhibit too much departure from normality based on visual inspection of sample summary statistics in table 1.

**Table1. descriptive statistics for price series at levels**

| Variable | Obs. | Mean | Std. Dev. | Skewness | Kurtosis |
|---|---|---|---|---|---|
| $\mathbf{P^B}$ | 1543 | 2.2546 | 0.5916 | 0.0563 | -0.5217 |
| $\mathbf{P^G}$ | 1543 | 2.2296 | 0.5682 | 0.0151 | -0.6112 |
| $\mathbf{F^G}$ | 1543 | 2.2574 | 0.5887 | 0.0896 | -0.5320 |
| $\mathbf{P^E}$ | 1543 | 2.2366 | 0.4533 | 1.1720 | 4.2681 |
| $\mathbf{F^E}$ | 1543 | 2.0884 | 0.3983 | 0.3895 | -0.3995 |
| $\mathbf{P^{RIN}}$ | 93 | 0.0245 | 0.0103 | -0.1873 | -0.6115 |

All of the series exhibit positive Skewness with the prices of ethanol having the largest positive Skewness of 1.17 followed by its futures price. In terms of their kurtosis, only ethanol spot price exhibits excessive kurtosis and RIN price exhibits lower kurtosis than that of normal distribution.

Since we have only 93 observations, the RIN prices are estimated using gasoline and ethanol futures and spot prices. RIN prices are first estimated using OLS regression, equation 5. Then, estimated coefficients are used with simulated price series, based on 292 weekly observations, to obtain RIN price.

$$P^{RIN} = \beta_0 + \beta_1 P^G + \beta_2 f^G + \beta_3 P^E + \beta_4 f^E + u \tag{5}$$

Estimated parameter coefficients are given in table 2:

**Table 2.** Estimated OLS coefficients for ethanol RIN prices

| Ethanol RIN | Coef. | \|t\| | P>\|t\| |
|---|---:|---:|---:|
| Intercept | 0.016696 | 2.55 | 0.013 |
| RBOB spot | -0.022767 | -2.00 | 0.049 |
| RBOB futures | 0.011543 | 1.10 | 0.275 |
| Ethanol spot | -0.030161 | -3.27 | 0.002 |
| Ethanol futures | 0.047698 | 4.33 | 0.00 |

R-square = 0.2427

## Empirical results and conclusion

Optimal hedge ratios are calculated with target expected no-hedge profit for RIN and 45 cent tax credit scenario and RIN only scenario. Optimal hedging strategy in the presence of ethanol RIN purchases and blenders' tax credit resulted in hedge ratio of h*=[-0.1, 1, 0.9]. This optimal hedging strategy tells that ethanol RIN is not purchased and the mandate is satisfied by blending 10% of ethanol where the remaining comes from non-oxygenated gasoline. It is optimal for the blender to hedge all of his ethanol purchases and take a speculative position in the amount of 10% of his non-oxygenated gasoline purchases.

In the no-tax-credit scenario, the optimal hedging strategy suggests a hedge ratio of h*=[0.05, 0.05, 0.91]. This strategy implies that in the absence of blenders' tax credit it is optimal for a gasoline blender to hedge only 5% of non-oxygenated gasoline and ethanol purchases and buy ethanol RIN in the amount of 10% his ethanol purchases.

Based on the obtained results, the RIN purchases do not reduce risk, hence, is not a good risk management tool in the presence of blenders' tax credits. However, in the absence of tax credit, RINs can be used as a risk management tool. The results are sensitive to accurate RIN price forecast, thus better modeling of the RIN prices is desired. Hierarchal nature of the RIN mandates and the ability to carry over the mandated amount to the next year adds more complexity to the modeling of RIN prices. Further separate study can be conducted to accomplish this task.

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