Thresholds and Regime Change in the Market for Renewable Identification Numbers.

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1. INTRODUCTION

The coupling of RIN prices appears to be the result of an ethanol market subject to RFS mandates that exceed the blend wall and non-binding mandates in the biodiesel market. It is thought that the ethanol mandate is binding beyond the market absorption ability, and thus the primary drivers of D6 ethanol RIN price are unobserved thresholds in renewable volume obligations, and deterministic variables such as corn price and ethanol blend margins. In regard to the market for biodiesel, the hypothesis is that biodiesel producers are over-complying with the RFS biodiesel mandates to meet an ethanol mandate which has crossed some threshold in proximity to the ethanol blend wall. Therefore biodiesel mandates are essentially non-binding.

Nonlinear threshold models are applied to address nonlinearities occurring in the prices. These types of models are well suited to handling nonlinearities and regime changes, such as those which occur with RFS revisions. A candidate set of models are fitted to the data and model selection techniques are carried out to determine the most appropriate fit.

Two key variables are thus proposed as threshold variables. In modeling D6 RIN prices, a variable is constructed to represent weekly renewable volume obligations for ethanol. This variable represents the weekly amount of ethanol blended into the national supply of gasoline. The variable is constructed by multiplying the annual percentage standard by weekly product supplied for gasoline. The annual percentage standard is the percentage of ethanol that must be blended into gasoline by producers or importers of gasoline. The percentage is set by the U.S. Environmental Protection Agency and is determined on an annual basis with revisions possible to occur year to year. The weekly product supplied for gasoline is provided by the U.S. Energy Information Association. . Weekly product supplied is an approximation of weekly consumption as it measures the disappearance of gasoline from primary sources such as refiners, blenders and distribution terminals (USDOE EIA 2016). In modeling D4 RIN prices, the proposed threshold variable is past values of D4 RIN price.

The Renewable Fuel Standard is implemented by requiring *Obligated Parties*, producers or importers of gasoline or diesel fuel, to meet four *Renewable Volume Requirements* (RVOs): (1) Total Renewable Fuel, (2) Advanced Biofuel, (3) Biomass-based Diesel, and (4) Advanced Cellulosic Biofuel. The RVOs are based on RFS percentages, which may be amended from year-to-year. The RFS percentages are the ratio of renewable fuels to all non-renewable gasoline and diesel fuels.

Obligated Parties demonstrate compliance with RVOs using a tracking system developed by the USEPA. In this system, every gallon qualifying as a renewable fuel produced or imported is assigned a renewable identification number (RIN), a 38-character numeric code which biofuel producers self-generate every time a gallon of qualifying renewable fuel is produced or imported. The RIN system was designed to provide a flexible way of meeting annual RVOs by Obligated Parties.

The type of RIN generated depends on the type of renewable fuel being produced, feedstock and production process. Each type of renewable fuel generates RINs which are denominated with different D-codes. Conventional biofuels (i.e. corn ethanol) generate D6 RINs, advanced biofuels (sugar cane ethanol) generate D5 RINs, biodiesel (biomass-based diesel) generates D4 RINs and cellulosic biofuels (cellulosic ethanol or cellulosic diesel) generate either D3 or D7 RINs. The D-codes, representing sub-mandates, are hierarchically nested. The nested nature of the sub-mandates means that biofuels that qualify for multiple RIN categories have a higher value. So, a D5 advanced biofuel RIN will be worth at least as much as a D6 conventional biofuel RIN and D4 biodiesel RINs will be worth at least as much as D5 advanced biofuel RINs. How much of a premium exists for D4 over D5 and D6 depends on the relative levels of advanced mandates versus conventional mandates and market equilibriums. Other factors affecting RIN prices include a speculative component. Non-obligated parties may participate in the RIN market by trading RINs much like any other commodity. Furthermore, obligated parties may either bank or borrow RINs, implying that RIN prices will capture market expectations. Prices also reflect current and expected marginal compliance costs, along with expected RFS mandates.

2. LITERATURE

Previous literature examining the RIN market is growing. Providing an early framework of the RIN market, Thompson et al. (2009) discuss core RIN values, and the hierarchal nature of RIN values. To demonstrate the core value of RINs, Thompson et al. (2010) use complementary slackness equations, and supply-and-use tables to simulate RIN price. McPhail et al. (2011), provide a conceptual model of RIN prices and discuss the factors affecting RIN price. Lade et al. (2015), show that prices reflect current and expected marginal compliance costs, along with expected RFS mandates.

As discussed in Lade et al. (2015), the coupling of the RINs suggests that the industry expectation was for biodiesel to be the marginal fuel pushing the industry beyond the blend wall and thus over-complying with the biodiesel mandates. In other words, the biodiesel mandates were no longer binding. This appears to suggest that the D4 core RIN value is essentially zero and only being supported by its nested characteristic which prevents the price from falling below D5 and D6 prices. This notion would support the hypothesis that D4 RIN prices are primarily driven by changes in D6 RIN price and regime changes in ethanol mandates, while D6 RIN prices are primarily driven by regime change in their own mandates, and deterministic variables, such as corn price and ethanol blending margin.

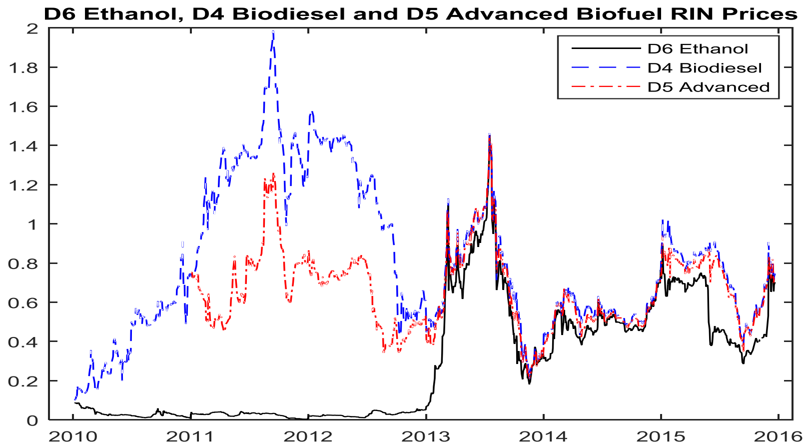
3. DATA

RIN price data is provided by EcoEngineers, a private consulting firm and project developer in the renewable energy sector. EcoEngineers provides comprehensive compliance management, market data, facility-planning and project development services for biofuel companies operating under US regulations. All price indices utilize volume-weighted averages either in the calculation of the index or as a component of the calculation of the Index. Weighted averages are utilized in an effort to minimize any trading anomalies or distress trading activity that might otherwise distort the data sample (EcoEngineers, 2012).

Data ranges from January 6 2010 to April 15 2016 for D4, D5 and D6 RIN credits. To examine the movements of these three RIN credits over time and in relation to each other it is useful to plot them together against time. Ethanol RINs began trading in April of 2008, biodiesel RINs began trading in September of 2009 and advanced biofuel RINs began trading in January of 2011 (Agricultural Marketing Resource Center (AGMRC)). Data in this study begins in January of 2010 when biodiesel RINs and ethanol RINs were trading at similar prices. The two prices diverged with biodiesel RINs trading at a premium over ethanol RINs between 2010 and 2013. The three RIN prices began to converge following jumps in D6 RIN value which began in early 2013. On January 2, the first trading day of 2013, the price of a D6 ethanol RIN was just seven cents. Over the next 41 trading days, D6 RINs jumped from 7 cents to 74 cents per RIN.

By March 4 2013, the D4 premium was just five cents and on December 5 2013 ethanol RINs eliminate the biodiesel RIN premium when D6 RINs trade almost two cents higher.

Figure 1



The D4 premium over D5 advanced biofuel RINs narrowed in October of 2012 when D4 is priced just eight cents over D5 on October 11 2013. Between the start of D5 trading in January of 2011 and October 10 2012, the average D4 premium was \$0.5677. This premium is to be expected from the nested nature of the RIN credits. Biodiesel RINs can be retired to meet biodiesel obligations, advanced biofuel obligations or ethanol blending obligations, so D4 Biodiesel RINs are expected to be worth at least as much as D5 and D6 RINs. The average D4 premium over D6 RINs between January 6 2010 and March 4 2013 is \$0.8758. The D4 premium over D5 from March 4 2013 to December 21 2015 averages \$0.0306, while the D4 premium over D6 during the same period averages \$0.1218. The convergence pattern is strongest between March 4 2012 and December 31 2014. The total spread is the sum of the individual spread between D4 and D6 and the spread between D4 and D5. During this period of strong convergence, the mean total spread is \$0.1068.

The first trading day of 2015, January 2, is responsible for a significant departure from the strong convergence pattern. On this day, D4 RIN prices increase by more than 10 cents per RIN, signaling the beginning of a weakly convergent pattern. From this point, the convergence is much weaker with the total spread between the three RIN prices calculated to be a mean of

$0.2435. The weakly convergent period is mostly attributable to diverging D6 ethanol RIN price, as D4 and D5 RINs continue to closely track each other in trading price.

Figure 2

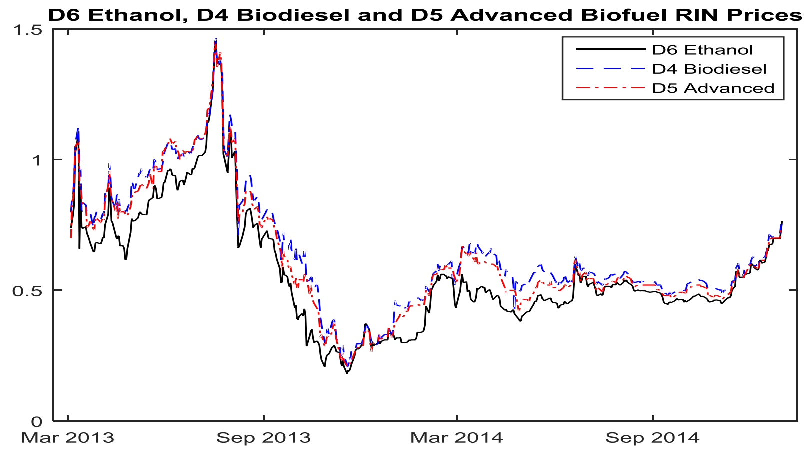
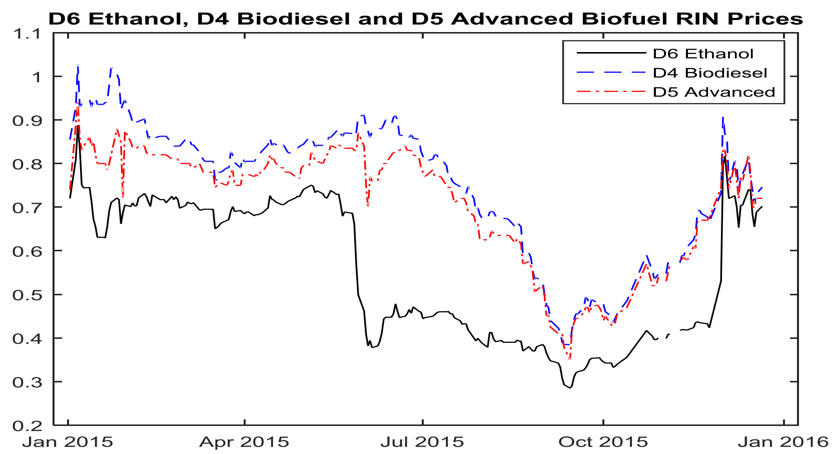


Figure 3



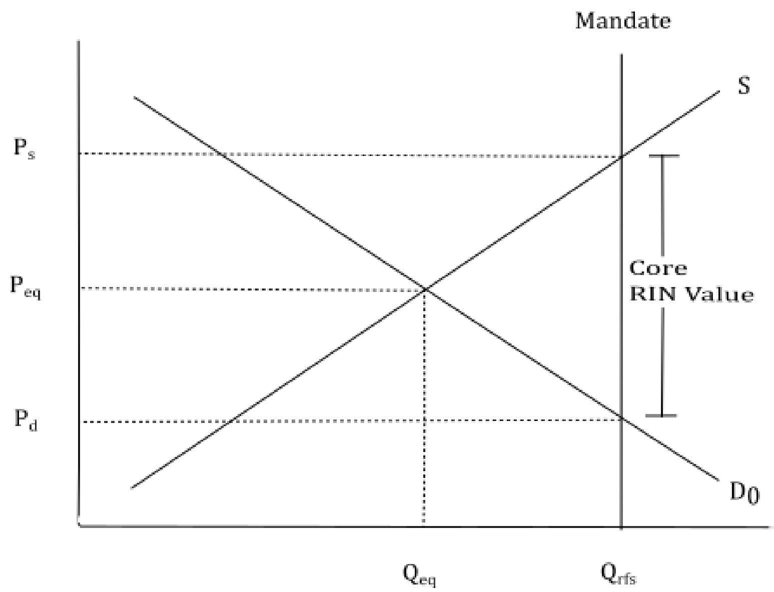
The convergence of ethanol, advanced biofuel and biodiesel RIN price is an interesting phenomenon. Understanding the fundamentals of the RIN market, drivers of RIN price and uncertainties in blending obligations help to determine the conditions under which RIN prices will significantly diverge in the future. A likely starting point is to understand what factors determine the convergence observed in 2013. It is clear from Figure 2, that a strengthened market for D6 ethanol RINs is not the only factor in the convergence. Prior to 2013, biodiesel

RINs are traded at a significant premium to advanced biofuel and conventional biofuel RINs. During the 2013 year, traders signal that all three RINs are nearly equal in value and it appears that the only difference in market price is attributable to the inherent nested structure of these three RINs.

4. RIN PRICING

The fundamental value, also known as the core value of a RIN, is determined by the gap-if positive-between the cost of supplying biofuel, and the price at which blenders are willing to pay for biofuel at mandated quantities. If there is no gap between the cost of supplying biofuel at the mandated quantity and the price blenders are willing to pay for RFS2-mandated quantities, then the market would be in equilibrium and there would be no need for the RIN markets. Disequilibrium necessitates the market for RINs and determines the value at which RINs are traded. RINs credits subsidize the biofuel market by providing an incentive for the market to trade at quantities greater than the market equilibrium when the mandate is not in place. When the mandate is binding, RIN prices are positive. When the mandate is non-binding, RIN prices are zero. A non-binding mandate implies renewable fuel production levels in equilibrium are greater than RFS mandated requirements, rendering the mandate superfluous. Conversely a binding mandate implies renewable fuel production levels in equilibrium are lower than RFS mandated requirements, necessitating the market for RINs. A binding mandate is necessary for a strong RIN market.

Figure 4: Core Value of RINs



Other factors affecting RIN prices include a speculative component. Non-obligated parties may participate in the RIN market by trading RINs much like any other commodity. If speculators anticipate an increase or decrease in RIN prices they may buy or sell excess RINs, further increasing or decreasing RIN prices. An example of a non-obligated party is a producer or importer with an output of less than 75,000 barrels per day, or producers or importers of jet fuel and other fuel s not falling under the umbrella of the RFS. Aside from the speculative component, other factors include feedstock prices, crude oil prices, and blender tax credits. The price of imports also impact RIN prices by causing a shift in the domestic supply of renewable fuels. When Brazilian sugarcane ethanol prices drop, the volume imported increases, increasing the supply of renewable ethanol domestically available and, thus, decreasing the price of RINs. Blender tax credits incentivize blending with more biofuels, increasing biofuel demand and decreasing RIN prices. Increases in crude oil prices also create stronger demand for alternative fuels, further incentivizing blending with biofuels and thereby reducing RIN value. Increased costs of feedstock production reduce feedstock supply and increase RIN value, while decreases in feedstock production costs increase feedstock supply and negatively affect the value of RINs.

The nested nature of the sub-mandates means that biofuels which qualify for multiple RIN categories have a higher value. So, an advanced biofuel RIN will be worth at least as much as a conventional biofuel RIN because advanced biofuel RINs count towards both the advanced biofuel RVO and the ethanol RVOs. Similarly, biodiesel D4 RINs will be worth at least as much as D5 advanced biofuel RINs because they count towards the advanced biofuel RVO and either the Biomass-based Diesel or the conventional ethanol RVOs. How much of a premium exists for D4 over D5 and D6 depends on the relative levels of advanced mandates versus conventional mandates and market equilibriums.

5. NONLINEARITY IN RIN PRICE

5.1 Visually inspecting for nonlinearity

One method of identifying nonlinearity in a time series Y_t is to examine the joint distribution of Y_t and Y_{t-1} or Y_{t-s} where $t \neq s$. If the two time series Y_t and Y_{t-s} are not jointly normal, there is evidence of nonlinearity. The Wold decomposition shows that the best linear predictor is the best one-step-ahead predictor if and only if innovation terms e_t satisfy the martingale condition. The martingale condition states that the conditional mean of e_t given e_{t-s} is identically equal to zero and this condition holds when e_t is a sequence of independent, identically distributed random variables with zero mean. Conversely, when the martingale condition fails, a nonlinear predictor will be the best one-step-ahead predictor. Given the Wold decomposition, the best linear predictor is approximated by finite ARIMA models. In linear ARIMA models, the errors are assumed to be independent and identically normally distributed. The normal error assumption implies the time series is also normally distributed and thus any two sets of time series are jointly normal. If the normality assumption is maintained and an ARIMA model results in a normally distributed process, then a nonlinear time series is generally not normally distributed. Therefore nonlinearity can be identified by finding a non-normal joint distribution of Y_t and Y_{t-s} . To perform this task, a scatter diagram of Y_t against Y_{t-s} is plotted (Cryer & Chan, 2008).

In the first case Y_t represents the log-differenced transformation of D4 biomass-based diesel RINs. In the second case Y_t represents the log-differenced transformation of D6 renewable fuel RINs. By taking the log-difference transformation, both series are stationary processes.

To aid in the visualization, a nonparametric nearest neighbor regression is fit to the data in each scatter plot. The nearest neighbor method fits locally weighted polynomial regression. Each nearest neighbor regression is specified as a first degree polynomial using 30% of the sample to calculate the bandwidth and local (Tricube) weighting. By weighting the observations, those points furthest from the local regression point are weighted less. Therefore the weighted regression minimizes the weighted sum of squared residuals providing a locally weighted scatterplot smoothing (Lowess) technique (Cleveland & Loader, 1996).

By fitting the nearest neighbor regression, the nonlinearity becomes more evident. In the case of D4 RIN series, the nonlinearity is particularly evident in the scatterplot of lags 1, 2 and 6. In the case of D6 RIN series the scatterplots and nearest neighbor fit also indicate nonlinearity in lags 1, 2 and 3.

Figure 5: Log-differenced D4 lag plots

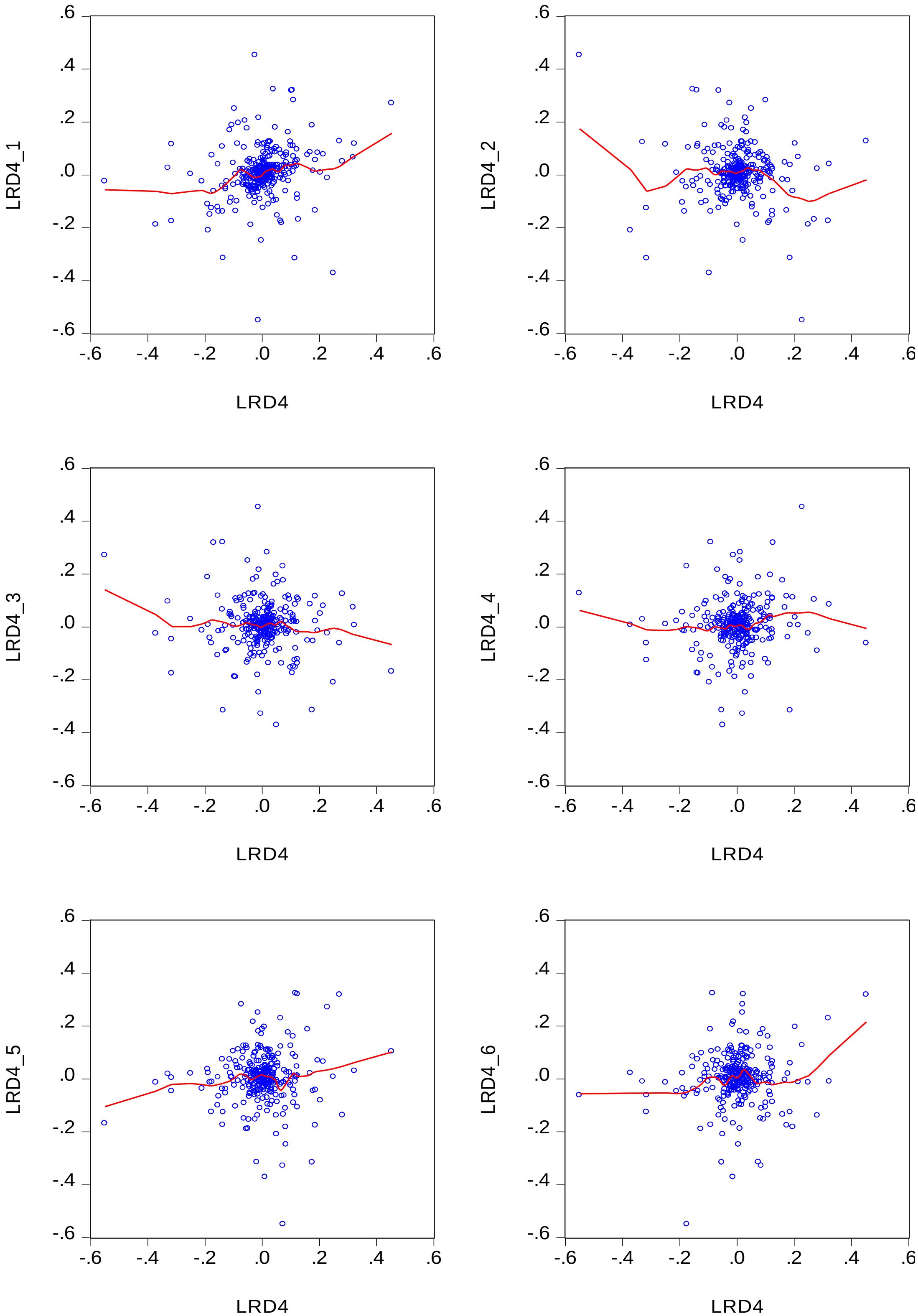
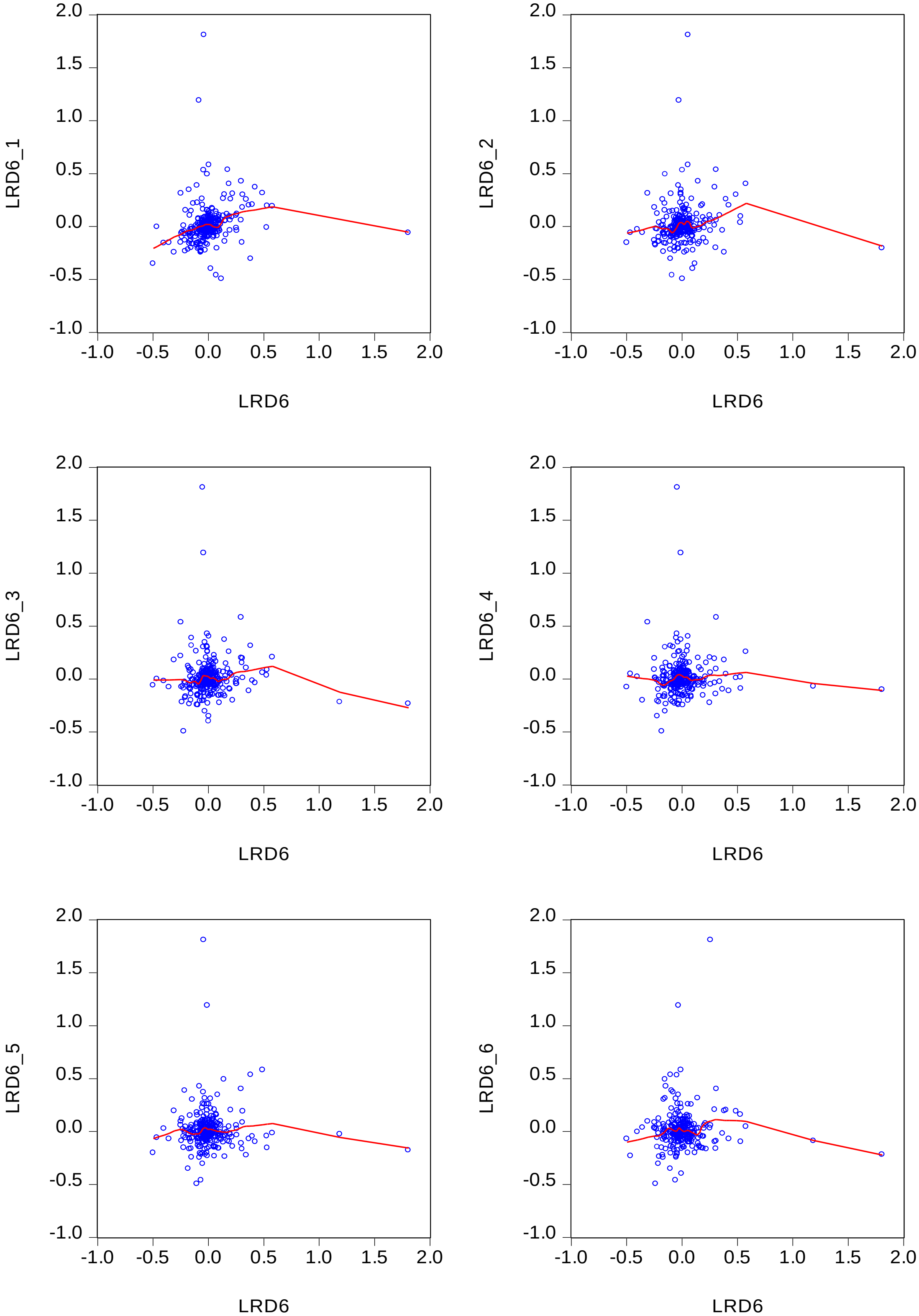


Figure 6: Log-differenced D6 lag plots



By plotting each time series multiple regimes can be observed. In the case of D4 RINs there appears to be at least three regimes of low, medium and high volatility. Similarly D6 RINs appear to exhibit multiple regimes with one regime displaying large jumps over short periods of observation. Surprisingly, or perhaps not, it appears the timing of regime change are shared among the D4 and D6 series.

Figure 7

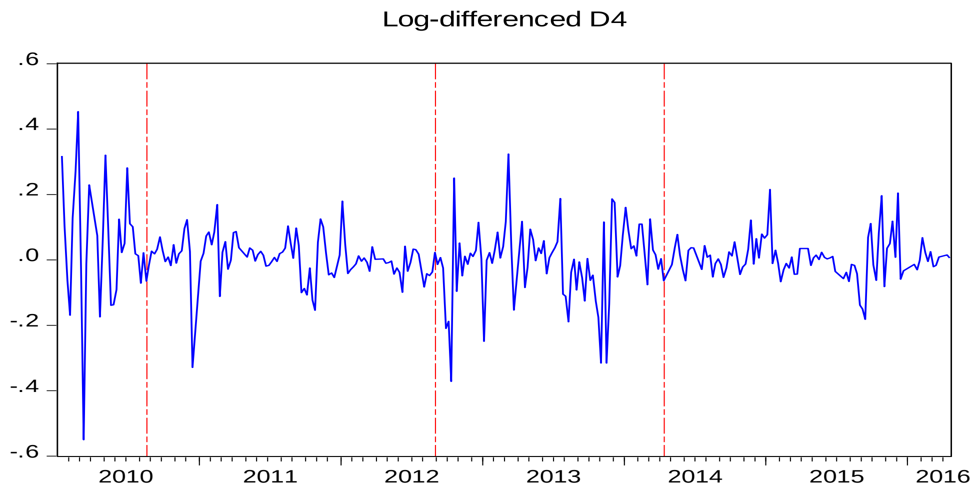
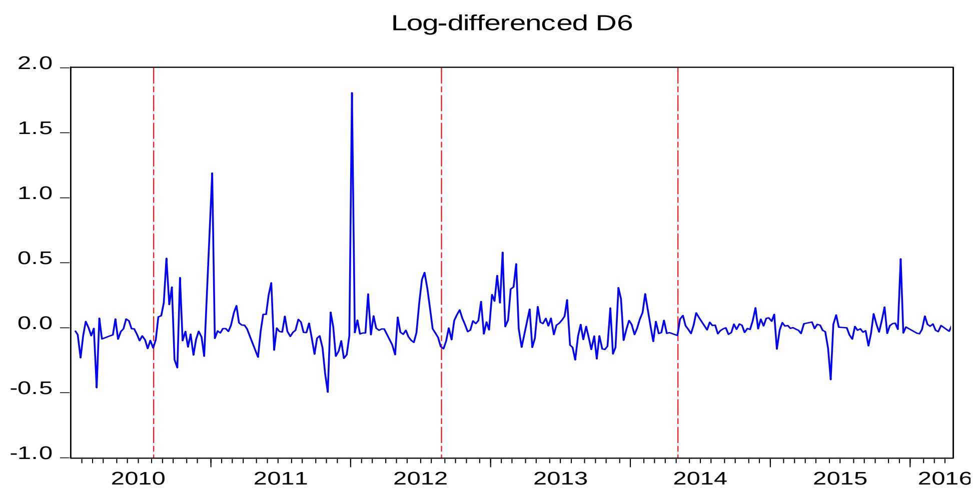


Figure 8



5.2 Testing for Nonlinearity

Beyond visual inspection, empirical tests provide further evidence of nonlinearity. Two particular tests have gained in popularity over the years, the test for quadratic nonlinearity, (Tsay, 1986), and a Tukey non-additive type test for nonlinearity (Keenan, 1985).

Keenan's test for nonlinearity is based upon a general form of nonlinear stationary time series models that are known as Volterra expansions (Cryer & Chan, 2008). Volterra expansions take the form

$$Y_t = \mu + \sum_{\mu=-\infty}^{\infty} \alpha_\mu \varepsilon_{t-\mu} + \sum_{\mu=-\infty}^{\infty} \sum_{v=-\infty}^{\infty} \alpha_{\mu v} \varepsilon_{t-\mu} \varepsilon_{t-v} + \sum_{\mu=-\infty}^{\infty} \sum_{v=-\infty}^{\infty} \sum_{w=-\infty}^{\infty} \alpha_{\mu v w} \varepsilon_{t-\mu} \varepsilon_{t-v} \varepsilon_{t-w} + \cdots$$

where $\{ \varepsilon_t, -\infty < t < \infty \}$ is a strictly stationary process, assumed to be independently and identically distributed with a zero mean. The right hand side terms in the expansion include an intercept, linear, quadratic and cubic terms. However, test of linearity is equivalent to a test of no multiplicative terms. So the null hypothesis tests whether or not higher order expansion terms vanish.

Keenan (1985), provides a three step process to estimate the test for nonlinearity.

(i) Regress Y_t on $\{1, Y_{t-1,}\, Y_{t-2}, \dots, Y_{t-p}\}$ where p is a predetermined lag order. Obtain the fitted values $\widehat{Y_t}$ and predicted residuals $\hat{e}_t$ for $t = p+1, \dots, n$ and calculate the sum of squared residuals $\hat{e_t}^2$.

(ii) Regress $\widehat{Y_t}^2$ on $\{1, Y_{t-1,}\, Y_{t-2}, \dots, Y_{t-p}\}$ and obtain the predicted residuals $\hat{\epsilon}_t$ for $t = p+1, \dots, n$.

(iii) Regress $\hat{e}_t$ on $\widehat{\in}_t$ with no intercept for $t = p+1, \dots, n$. This allows the user to obtain $\hat{\eta} = \hat{\eta}_0 \sqrt{\sum_{t=p+1}^{n} \hat{\epsilon}_t^2}$ $\hat{\eta}_0$ is the regression coefficient.

Keenan's test statistic is thus

$$\hat{F} = \frac{\hat{\eta}^2 (n - 2p - 2)}{\hat{e_t}^2 - \hat{\eta}^2}$$

Under the null hypothesis of linearity $\hat{F}$ approximately follows an F-distribution with degrees of freedom 1 and $n - 2p - 2$. Keenan's test is equivalent to testing that the coefficient $\hat{\eta} = 0$ in the regression model

$$Y_t = c + \beta_1 Y_{t-1} + \beta_p Y_{t-p} + \exp\left\{\eta\left(\sum_{j=1}^{p} \beta_j Y_{t-j}\right)^2\right\} + \varepsilon_t.$$

If the coefficient η equals zero, then $\exp(0) = 1$ and the model simply becomes an AR (p).

Tsay (1986), extended Keenan's test improving the power of the test to account for more general nonlinear terms. These more general terms are accounted for by

replacing $\exp\left\{\eta\left(\sum_{j=1}^{p} \beta_j Y_{t-j}\right)^2\right\}$ with

$$\begin{gathered}\exp\{\delta_{1,1}Y_{t-1}^2 + \delta_{1,2}Y_{t-1}Y_{t-2} + \cdots \delta_{1,p}Y_{t-1}Y_{t-p} + \cdots \\ +\delta_{2,2}Y_{t-2}^2 + \delta_{2,3}Y_{t-2}Y_{t-3} + \cdots \delta_{2,p}Y_{t-2}Y_{t-p} + \cdots \\ \delta_{p-1,p-1}Y_{t-p+1}^2 + \delta_{p-1,p}Y_{t-p+1}Y_{t-p} + \delta_{p,p}Y_{t-p}^2\}\,.\end{gathered}$$

The null hypothesis in Tsay's test is that all coefficient terms $\delta_{i,j}$ are equal to zero. The test statistic follows an F-distribution and thus an F-test that all $\delta_{i,j}{}'s$ equal zero tests the null hypothesis that the true process is linear.

The following table summarizes the test results for both the Keenan and Tsay tests for linearity.

Table 1: Tsay and Keenan tests for nonlinearity

Log-differenced D4				Log-differenced D6			
Test	AR(p)*	F-stat	p-value	Test	AR(p)*	F-stat	p-value
Tsay	1	6.98	0.0086	Tsay	1	8.0260	0.0049
Keenan	1	6.22	0.0132	Keenan	1	7.8965	0.0053

*AR (p) lag orders are estimated by fitting an autoregressive model, choosing the lag order which minimizes Akaike's information criteria (AIC).

The null hypothesis of linearity in the log-differenced D4 series is rejected with p-values of 0.0086 and 0.0132 in the Tsay and Keenan tests. Similarly, the null the hypothesis of linearity in the log-differenced D6 series is rejected in both the Tsay and Keenan tests with associated p-values of 0.0049 and 0.0053 respectively. Therefore, both series are concluded to exhibit nonlinearity.

6. THRESHOLDS IN THE RIN MARKET

6.1 Testing for Threshold Nonlinearity

A central hypothesis in this paper is that coupling patterns observed in the RIN market are brought about by some proximity to the ethanol blend wall. In other words, there is some unobservable threshold, that when crossed, brings about a change in the behavior of the RIN market. Therefore a key variable in this paper is weekly renewable volume obligations for producers and importers of gasoline. The variable is constructed by multiplying the annual renewable fuel standard percentages by weekly gasoline product supplied. Weekly product supplied is an approximation of weekly consumption because it measures the disappearance of gasoline from primary sources such as refiners, blenders and distribution terminals (USDOE EIA 2016). The ethanol blend wall is generally thought to be 10 percent of gasoline consumption. Weekly renewable volume obligations estimate the weekly volume of ethanol blended into the nation's gasoline supplies. Where this observed data lies in relation to some unobserved threshold is presumed to trigger regime changes in the D6 renewable fuel RIN price. This type of model is called a threshold autoregressive (TAR) model.

Prices for D4 biomass-based diesel RINs are thought to be driven primarily by biodiesel blend margins and other market forces unrelated to the ethanol blend wall. Therefore the primary threshold variable is not expected to be the weekly renewable volume obligations for ethanol.

Rather, it is hypothesized that regime changes in D4 RIN prices are triggered by endogenous factors to the D4 RIN market. Therefore the key threshold variable becomes lagged values of D4 RIN price. This type of model is called a self-exciting threshold autoregressive (SETAR) model.

To test for the presence of threshold nonlinearities, (Chan, 1990) developed a likelihood ratio test to determine if TAR models provide a significantly better fit than linear AR models.

A two-regime TAR model takes the form

$$Y_t = \begin{Bmatrix} \beta_{0,1} + \beta_{1,1}Y_{t-1} + \cdots + \beta_{p_1,1}Y_{t-p_1} + \sigma_1\varepsilon_t, & if\ Z_{t-d} \leq r \\ \beta_{0,2} + \beta_{1,2}Y_{t-1} + \cdots + \beta_{p_2,1}Y_{t-p_2} + \sigma_2\varepsilon_t, & if\ Z_{t-d} > r \end{Bmatrix}$$

where Z_{t-d} is the threshold variable. In the SETAR model Z_{t-d} is equivalent to Y_{t-d}. The null hypothesis in the likelihood-ratio test for threshold nonlinearity is that $\beta_{0,2} = \beta_{1,2}Y_{t-1} = \cdots = \beta_{p_2,1} = 0$. In practice it assumed that $d \leq p$ and the LR-test statistic is equivalent to

$$LR_n = (n-p)log\left\{\frac{\hat{\sigma}^2(H_0)}{\hat{\sigma}^2(H_1)}\right\}$$

where $\hat{\sigma}^2(H_0)$ is the maximum likelihood estimation of the noise variance from the linear AR(p) fitted model and $\hat{\sigma}^2(H_1)$ from the TAR fit. Under the null, the threshold parameter is absent (Cryer & Chan, 2008). The test depends on the interval over which the threshold is being searched. This interval is defined as $a * 100th$ percentile to the $b * 100th$ percentile of the time series data. It is necessary to restrict the threshold search over this interval to prevent threshold estimators that are close to the minimum or maximum tails of the time series. A threshold estimator very close to the minimum or maximum tail of a time series would results in too few observations in the resulting regime.

The test for threshold nonlinearity is carried out for the D4 and D6 series. For purposes of this test, the lag order (p) is set to 1 lag, and the test is estimated while allowing the delay parameter

(d) to vary from 1 to 8. The interval is restricted to the 25th percentile and 75th percentile of the D4 time series.

Table 2: Test for Threshold Nonlinearity with lag order 1

Test for Threshold Nonlinearity in biomass-based diesel D4 RIN series								
delay	1	2	3	4	5	6	7	8
LR-stat	15.53	9.94	3.51	18.81	8.47	9.002	14.603	11.14
P-value	0.0086	0.0795	0.3245	0.0021	0.1321	0.1105	0.0127	0.0507

The presence of threshold nonlinearity is detected in several cases, where the delay parameter takes on values of one, four, seven and eight. Therefore, the null hypothesis is rejected and the log-transformed D4 price series is concluded to have significant nonlinearity. Next, the log-transformed D6 price series is tested using the same specification as above.

Table 3: Test for Threshold Nonlinearity with lag order 1

Test for Threshold Nonlinearity in renewable fuel D6 RIN series								
delay	1	2	3	4	5	6	7	8
LR-stat	4.1673	17.69	9.332	10.771	6.6976	6.5844	13.55	7.029
P-value	0.3351	0.0034	0.0984	0.0583	0.2209	0.2265	0.0196	0.2006

Testing for threshold nonlinearity in the D6 RIN series results in the null hypothesis being rejected in two cases. Based on the test results in Table 3, the log-transformed D6 price series is concluded to have significant threshold nonlinearity.

6.2 Estimation of SETAR and TAR models

The two-regime threshold autoregressive model is defined as

$$Y_t = \begin{Bmatrix} X'\delta_1 + \beta_{1,1}Y_{t-1} + \cdots + \beta_{p_1,1}Y_{t-p_1} + \sigma_1\varepsilon_t, & if\ Z_{t-d} \leq r \\ X'\delta_2 + \beta_{1,2}Y_{t-1} + \cdots + \beta_{p_2,1}Y_{t-p_2} + \sigma_2\varepsilon_t, & if\ Z_{t-d} > r \end{Bmatrix}.$$

The autoregressive lag orders of the two sub models are not necessarily identical and are thus labeled as p_1 and p_2. Other regime specific variables are in the vector X and the coefficient

$\delta_j$varies among regimes where. Extending the two-regime model to any m regimes is done by further partitioning the thresholds so that $-\infty < r_1 < r_2 < \cdots r_{m-1} < \infty$. The location of Z_{t-d} in relation to the thresholds will determine the sub models. For example a four regime threshold autoregressive model is represented as the piecewise regression of

$$Y_t = \begin{Bmatrix} X'\delta_4 + \beta_{1,4}Y_{t-1} + \cdots + \beta_{p_4,4}Y_{t-p_4} + \sigma_4\varepsilon_t, & r_3 \leq Z_{t-d} \\ X'\delta_3 + \beta_{1,3}Y_{t-1} + \cdots + \beta_{p_3,3}Y_{t-p_3} + \sigma_3\varepsilon_t, & r_2 \leq Z_{t-d} < r_3 \\ X'\delta_2 + \beta_{1,2}Y_{t-1} + \cdots + \beta_{p_2,2}Y_{t-p_2} + \sigma_2\varepsilon_t, & r_1 \leq Z_{t-d} < r_2 \\ X'\delta_1 + \beta_{1,1}Y_{t-1} + \cdots + \beta_{p_1,1}Y_{t-p_1} + \sigma_1\varepsilon_t, & Z_{t-d} < r_1 \end{Bmatrix}.$$

An indicator function $I_j(Z_{t-d}, r_j)$ where $j = 1,2,3, \dots m$, which takes the value of 1 if the expression is true and zero if false, can be used to combine the piecewise regression. The above piecewise regression of four regimes can be combined into a single nonlinear regression of

$$\begin{aligned} Y_t = \{ & (X'\delta_1 + \beta_{p_1,1}Y_{t-p_1} + \sigma_1\varepsilon_t)I_1(Z_{t-d}, r_1) + (X'\delta_2 + \beta_{p_2,2}Y_{t-p_2} + \sigma_2\varepsilon_t)I_2(Z_{t-d}, r_1, r_2) \\ & + (X'\delta_3 + \beta_{p_3,3}Y_{t-p_3} + \sigma_3\varepsilon_t)I_3(Z_{t-d}, r_2, r_3) + (X'\delta_4 + \beta_{p_4,4}Y_{t-p_4} \\ & + \sigma_4\varepsilon_t)I_4(Z_{t-d}, r_3)\}. \end{aligned}$$

The identity of the specification is determined by the threshold variable Z_{t-d}. If Z_{t-d} is the *d-th* lagged dependent variable then the model is a self-exciting threshold autoregressive (SETAR) model. If Z_{t-d} is some other exogenous variable then the model becomes the conventional threshold autoregressive (TAR) model.

The problem is therefore to estimate the coefficients δ_j , $\beta_{p_j,j}$ and the threshold values r_j. To do so nonlinear least squares is performed to minimize the sum of squares objective function. The least square estimator $\hat{\theta} = \left(\hat{\delta}_j, \hat{\beta}_{p_j,j}, \hat{r}_j\right)$ solves the minimization problem

$$\begin{aligned} \hat{\theta} = argmin \sum_{t=1}^{n} \{ & Y_t - \left(X'\delta_1 + \beta_{p_1,1}Y_{t-p_1}\right)I_1(Z_{t-d}, r_1) - \cdots - (X'\delta_4 \\ & + \beta_{p_4,4}Y_{t-p_4})I_4(Z_{t-d}, r_3)\}^2 . \end{aligned}$$

6.3 Model Selection for renewable fuel D6 RIN time series

The first step in building a nonlinear model whether the resulting model is a TAR, STAR or SETAR, is to specify a linear model to form a starting point for further analysis. The proposed linear model for D6 RINs is one of lagged dependent variables, and three exogenous variables including, ethanol blend margins, end of week corn prices and D4 RIN prices. Ethanol blend margins are defined as the difference between wholesale ethanol price and wholesale gasoline price, plus applicable blend credits for the time periods when such tax incentives were in effect. The blend margins are thought to approximate the core value of RINs as depicted in Figure 8. Corn prices are for nearest future contract price at end of week closing price on the Chicago Board of Trade exchange. Biodiesel D4 RIN prices are included to capture the nested structure and relationship of the two RIN prices. When blending mandates are pushed beyond the blend wall, ethanol RINs should be in high demand and in fact there may be a deficit of available D6 RINs to fulfill the ethanol mandate. If that is the case, the deficit may be made up by submitting D5, D4, D3 or D7 RINs as discussed earlier. In this state of the world, D6 RIN prices ought to be driven to their ceiling, which is defined by the floor of D5 and D4 RIN prices. Since D5 RIN prices are bounded by D6 and D4 RINs, they are excluded from the analysis. Therefore D4 RINs prices should be highly correlated with D6 RIN prices, at least in certain regimes. The aim of this study is to determine when the transition between regimes is made, and which transition variable (or threshold variable) is most significant in explaining the regime change.

First the optimal lag length of D6 RIN series is determined using an iterative process where the optimal lag is chosen to minimize Akaike's Information Criteria (AIC).

Table 4: D6 Lag Selection

D6 RIN AR-Order	Akaike's Information Criteria
0.000000	-0.525712
1.000000	-0.544843
2.000000	-0.538805
3.000000	-0.532636
4.000000	-0.526221
5.000000	-0.519637
6.000000	-0.512976
7.000000	-0.506842
8.000000	-0.503419
9.000000	-0.511798
10.00000	-0.505944

With a lag length of one selected to minimize the AIC, the linear model is estimated via ordinary least squares.

Table 5: Linear model of D6 RIN price

Dependent Variable: LRD6
Method: Least Squares
Included observations: 278 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LRD6(-1)	0.130925	0.051442	2.545076	0.0115
ETHMRGN	0.009565	0.017389	0.550088	0.5827
DLCORN	0.017965	0.225647	0.079614	0.9366
LRD4	0.572233	0.097061	5.895577	0.0000

R-squared	0.139290	Mean dependent var	0.008203
Adjusted R-squared	0.129866	S.D. dependent var	0.175814
S.E. of regression	0.164001	Akaike info criterion	-0.763609
Sum squared resid	7.369559	Schwarz criterion	-0.711413
Log likelihood	110.1417	Hannan-Quinn criter.	-0.742669
Durbin-Watson stat	1.910228		

From the linear model D4 RIN prices are highly significant and positively related to D6 RIN prices. While ethanol blend margins and end of week corn prices are not statistically significant they remain in the model as this result may change under different regimes.

Before proceeding with any model selection a test for conditional heteroskedasticity in the AR (p) is performed. The presence of heteroskedasticity is likely to have a significant effect on inference and thus model selection results. An autoregressive conditional heteroskedasticity (ARCH) test is carried out by regressing the squared residuals on lagged values of the squared residual. However, the presence of serial correlation will invalidate any ARCH test so a Breusch-Godfrey test for serial correlation is first performed. The null hypothesis is of no serial correlation in residuals up to a specified lag order. In this case tests are carried out for second-order serial correlation.

Table 6

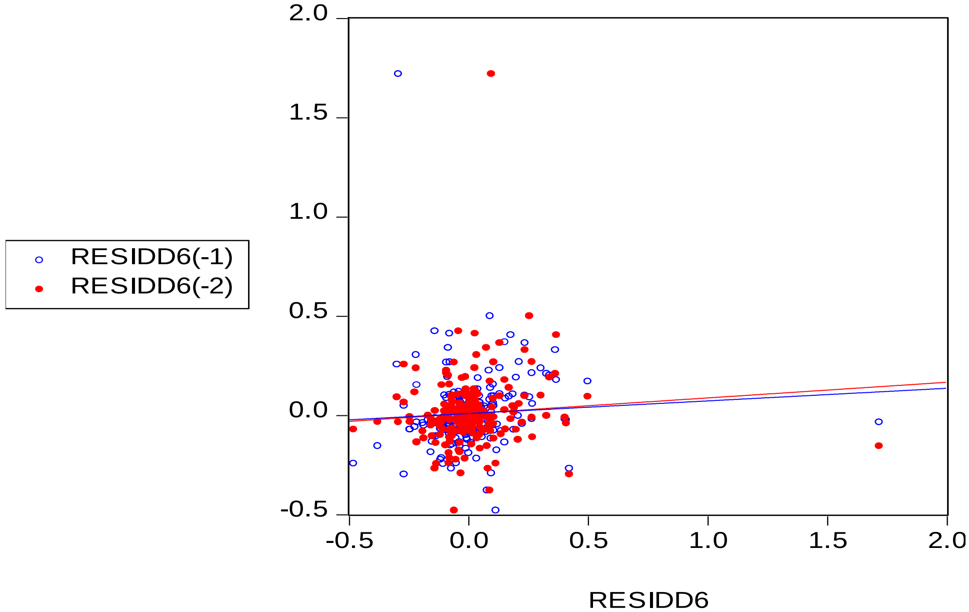
Breusch-Godfrey Serial Correlation LM Test:

F-statistic	4.150832	Prob. F(2,272)	0.0168
Obs*R-squared	8.233496	Prob. Chi-Square(2)	0.0163

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Included observations: 272

Table 6 indicates a failure to reject the null hypothesis of second-order serial correlation in D6 RINs. One way to visualize serial correlation is to generate a scatter plot of residuals against lagged values.

Figure 9: Visualizing Possible Serial Correlation



Plotting the residuals against lagged values is particularly useful in the case of extreme outliers, which is precisely the case here. Figure 9, depicts the relationship between D6 residuals and their lagged values. Contrary to the Breusch-Godfrey test results, the residuals do not appear to be strongly correlated with their lagged values. However, there are several outliers which may cause misleading inference in B-G tests. (Ann & Midi, 2011). The presence of large outliers in the residual terms motivates a test for higher order serial correlation. Testing for fourth-order serial correlation results in a p-value of 0.1018 signaling a failure to reject the null hypothesis of no serial correlation of the fourth-order. Another method of detecting serial correlation is to plot the autocorrelation function and partial autocorrelation function.

Figure 10: Correlogram of residuals for D6 Linear Model

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.069	0.069	1.3227	0.250
		2	0.080	0.076	3.1319	0.209
		3	-0.020	-0.030	3.2440	0.356
		4	-0.004	-0.007	3.2479	0.517
		5	-0.029	-0.024	3.4852	0.626
		6	0.024	0.028	3.6468	0.724
		7	-0.019	-0.019	3.7508	0.808
		8	0.066	0.064	5.0228	0.755
		9	-0.143	-0.151	10.975	0.277
		10	-0.048	-0.040	11.648	0.309
		11	-0.006	0.028	11.660	0.390
		12	0.031	0.031	11.935	0.451

Figure 10 shows the empirical pattern of correlation between residuals and their own past values. As can be seen, all autocorrelation and partial autocorrelation values are near zero and all Q-statistics are insignificant. This provides more evidence that the linear model for D6 RINs does not actually suffer from serial correlation. With no serial correlation tenable, tests for heteroskedasticity are carried out.

Table 7 reports the results of the test for first-order autoregressive conditional heteroskedasticity. Results strongly indicate the null hypothesis of homoscedasticity cannot be rejected. Therefore it is concluded that D6 RINs do not suffer from conditional heteroskedasticity.

Table 7: D6 test for ARCH

Heteroskedasticity Test: ARCH

F-statistic	0.131655	Prob. F(1,263)	0.7170
Obs*R-squared	0.132590	Prob. Chi-Square(11)	0.7158

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Included observations: 265 after adjustments

The proposed model for the D6 RIN series is a threshold autoregressive model with exogenous variables. The proposed threshold parameter for D6 RIN price is weekly renewable volume obligation (rvo) defined earlier. Log-transforming the weekly rvo ensures stationarity. This model will be tested against the competing SETAR model, where the threshold variable is the endogenous lagged dependent variable. First, the best fitting threshold delay parameter is chosen for the transition variable RVO. The delay parameter is allowed to vary from 0 to 5 while specifying the model and choosing the delay parameter which minimizes the sum of squared residual (SSR). While setting the maximum number of possible regimes to four, the delay parameter which minimizes the SSR is $ln(rvo)_{t-2}$ with a SSR of 5.102857.

In the SETAR model, the threshold variable is the endogenous lagged dependent variable. Before testing the TAR model against the SETAR model, the best fitting delay parameter for lagged values of D6 are found by minimizing the SSR of the null hypothesized SETAR model. The delay parameter is allowed to vary from 0 to 5 while specifying the model and choosing the delay parameter which minimizes the SSR. Again the maximum number of regimes is set to four and the models are iteratively estimated, capturing the SSR for each specification. In this case the best fitting threshold variable for the SETAR model is found to be $dln(d6)_{t-2}$ with a SSR of 5.335060.

Next, the number of thresholds for each model is determined. Visual inspection of Figure 6 indicates there are possibly four regimes in the D6 RIN series, but not likely to exceed four. However it is possible there is less than four regimes and to determine this, a sequential estimation of the number of thresholds and the associated threshold values is performed (Bai & Perron, 1998).

In the case of the TAR model with the exogenous threshold variable of $dln(rvo)_{t-2}$ the maximum number of thresholds is set to three, thus limiting the maximum number of regimes to four. However, using the Bai-Perron method of L+1 vs L sequentially determined thresholds, it is found that only two thresholds and thus three regimes are chosen. In Table 4 the threshold specification is summarized. The table reports the estimated number of thresholds and the associated threshold values.

Table 8

Summary of Threshold Specification
Threshold variable: LRVO(-2) Estimated number of thresholds: 2 Method: Bai-Perron tests of L+1 vs. L sequentially determined thresholds Maximum number of thresholds: 3 Thresholds values estimated: -0.2984065, -0.215888

When specifying the TAR model for D6 RIN prices, the threshold specification indicates there are two thresholds and thus three regimes. In the case of the SETAR model, the maximum number of thresholds is again set to 3, limiting the possible number of regimes to four. Using the same Bai-Perron sequential estimation, the number of thresholds is estimated to be two, thus predicting three regimes.

Table 9

Summary of Threshold Specification
Threshold variable: LRD6(-2) Estimated number of thresholds: 1 Method: Bai-Perron tests of L+1 vs. L sequentially determined thresholds Maximum number of thresholds: 3 Threshold value used: -0.09779775

The next task is to determine whether the TAR model or the SETAR model is a better fit for the D6 RIN series. To do so, each model is specified with the established delay parameters, and number of thresholds found in the threshold specifications. The model which minimizes the sum of squared residuals is deemed to be the best fitting model for D6 RINs. Results indicate the TAR with three regimes (TAR (3)) significantly outperforms the SETAR with two regimes (SETAR (2)). The TAR (3) model results in a SSR of 5.708684, while the SETAR (2) results in a SSR of 6.099091.

Table 10

Threshold Variable	SSR	Regimes
LRVO(-2)	5.708684	3
LRD6(-2)	6.099091	2

Table 10 reports the associated SSR for each model. Based on these results the exogenous threshold variable of weekly renewable volume obligations outperforms endogenous lagged values of the dependent variable.

The model of choice for D6 RINs is

$$\begin{aligned} Y_t = \{\beta_0 &+ \left(X'\delta_1 + \beta_{p_1,1}Y_{t-p_1} + \varepsilon_t\right)I_1(Z_{t-d} < r_1) \\ &+ \left(X'\delta_2 + \beta_{p_2,2}Y_{t-p_2} + \varepsilon_t\right)I_2(r_1 \leq Z_{t-d} < r_2) \\ &+ \left(X'\delta_3 + \beta_{p_3,3}Y_{t-p_3} + \varepsilon_t\right)I_3(r_2 \leq Z_{t-d})\} \end{aligned}$$

$$X = \text{vector of exogenous variables}$$

$$Z_{t-d} = \log - \text{transformed renewable volume obligation}$$

$$r_j = \text{threshold values where } j = 1{:}\,2$$

$$I_m = \text{indicator variable equal to one if the argument is true, where } m = 1{:}\,3$$

$$\beta_0 = \text{intercept term assumed constant across regimes}$$

$$Y_{t-p_m} = \text{lagged dependent variables where } m = 1:3$$

Notice that the order of lagged dependent variable is allowed to vary between regimes. The model is estimated assuming a lag order of one in each regime, but there is nothing to prevent the lag order to vary between regimes. Also notice that m represents the number of regimes. The vector of exogenous variables includes ethanol blend margins, D4 RIN price, and end of week corn price. End of week corn prices are log-differenced to ensure stationarity, however ethanol blend margins were found to be stationary without transformation.

6.4 Model Selection for biomass-based diesel D4 RIN time series

Similar to the linear model for D6 RIN prices the linear model for D4 RIN price is specified with three exogenous variables including biodiesel blend margin, end of week soybean price and D6 RIN price. Motivation for the choice of exogenous variables are similar to those of D6 RIN prices. The optimal lag length is chosen and the linear model is estimated using ordinary least squares. As was the case with D6 RINs the optimal lag length is found to be of lag order one.

Table 11: D4 Lag Selection

D4 RIN AR-Order	Akaike's Information Criteria
0.000000	-2.116010
1.000000	-2.142083
2.000000	-2.134952
3.000000	-2.127835
4.000000	-2.134066
5.000000	-2.129076
6.000000	-2.122169
7.000000	-2.115057
8.000000	-2.108795
9.000000	-2.102204
10.00000	-2.096068

With a lag length of one selected to minimize the AIC, the linear model is estimated via ordinary least squares.

Table 12: Linear Model of D4 RIN price

Dependent Variable: LRD4
Method: Least Squares
Included observations: 271 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LRD4(-1)	0.191933	0.055036	3.487388	0.0006
BDMRGN	0.003367	0.006705	0.502152	0.6160
DLSOY	-0.077259	0.152564	-0.506405	0.6130
LRD6	0.170539	0.028903	5.900316	0.0000

R-squared	0.153066	Mean dependent var	0.004856
Adjusted R-squared	0.143550	S.D. dependent var	0.091734
S.E. of regression	0.084895	Akaike info criterion	-2.080147
Sum squared resid	1.924324	Schwarz criterion	-2.026979
Log likelihood	285.8599	Hannan-Quinn criter.	-2.058799
Durbin-Watson stat	1.851852		

Table 12 reports the results of the proposed linear model of D4 RIN price. Similar to the linear model of D6 RIN price, only the lagged dependent variable and D6 RIN price is statistically significant. Although the biodiesel blend margin and end of week soybean prices are not statistically significant, they remain in the model as this result may change under different regimes.

Tests for serial correlation and autoregressive conditional heteroskedasticity are performed before proceeding with any nonlinear model selection procedures. The test for serial correlation is carried out by regressing the AR (1) residuals on the lagged value of D4, plus two lagged residuals, thus testing for second-order serial correlation. Table 13 reports the results of the second-order serial correlation test. With a p-value of 0.2004 the null hypothesis of no serial correlation cannot be rejected, and it is concluded that D4 RINs do not suffer from serial correlation.

Table 13

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.617083	Prob. F(2,265)	0.2004
Obs*R-squared	3.267514	Prob. Chi-Square(2)	0.1952

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Included observations: 271

Table 14 reports the results of the autocorrelation conditional heteroskedasticity test for the D4 time series. With a p-value of 0.0000 the null hypothesis of homoscedasticity is rejected. Therefore it is concluded that D4 RIN prices suffer from conditional heteroskedasticity.

Table 14

Heteroskedasticity Test: ARCH

F-statistic	18.32108	Prob. F(1,256)	0.0000
Obs*R-squared	17.23105	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Included observations: 88 after adjustments

Correcting for conditional heteroskedasticity is done by specifying Newey-West standard errors which correct for heteroskedasticity and autocorrelation (HAC). Estimating the linear model with Newey-West standard errors does not significantly change the outcome of statistical significance for the explanatory variables.

Table 15: HAC corrected Linear Model of D4 price

Dependent Variable: LRD4
Method: Least Squares
Included observations: 271 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LRD4(-1)	0.191933	0.062164	3.087521	0.0022
BDMRGN	0.003367	0.006076	0.554145	0.5799
DLSOY	-0.077259	0.131455	-0.587725	0.5572
LRD6	0.170539	0.046437	3.672462	0.0003

R-squared	0.153066	Mean dependent var	0.004856
Adjusted R-squared	0.143550	S.D. dependent var	0.091734
S.E. of regression	0.084895	Akaike info criterion	-2.080147
Sum squared resid	1.924324	Schwarz criterion	-2.026979
Log likelihood	285.8599	Hannan-Quinn criter.	-2.058799
Durbin-Watson stat	1.851852		

The proposed model for D4 RIN series is the self-exciting threshold autoregressive model with exogenous variables (SETAR). The proposed threshold variable is lagged values of the dependent variable D4 RIN price, hence the name self-exciting. However, a competing threshold variable will be introduced to test against the alternative. The competing threshold variable is the lagged values of renewable D6 RIN price. Due to the nested structure of RINs, the price of D4 RINs should always be worth at least as much as D6 RINs as discussed earlier. Due to the ethanol blend percentage standards nearing the ethanol blend wall, obligated parties may over comply with the biodiesel annual standards in order to generate D4 RINs which are worth 1.5 D6 RINs. By over complying, the biodiesel blending mandate may effectively be nonbinding, which would drive the price of D4 RINs down to until there in an effective zero premium over D6 RINs. If that is indeed the case, then one would expect the price of D6 RINs to be a suitable threshold variable for the D4 RIN price series.

First, the best fitting threshold delay parameter is chosen for the lagged dependent variable. The delay parameter is allowed to vary from 1 to 5 while specifying the model and choosing the delay parameter which minimizes the sum of squared residual (SSR). While setting the maximum number of possible regimes to four, the delay parameter which minimizes the SSR is $dln(d4)_{t-3}$ with a SSR of 1.643880. This process is repeated while specifying the external threshold of lagged D6 prices. Again the maximum number of possible regimes is four and the delay parameter is allowed to vary between 1 and 5. The lagged value of D6 price which minimizes the SSR is found to be $dln(d6)_{t-3}$ with a SSR of 1.757713.

Visual inspection of Figure 5 indicates there are possibly four regimes in the D4 RIN series, similar to the D6 RIN series. However it is possible there are less than four regimes and to determine this, a sequential estimation of the number of thresholds and the associated threshold values is performed using the Bai-Perron method of L+1 vs L sequentially determined thresholds. In the case of the SETAR model with a $dln(d4)_{t-3}$ as the threshold variable, two thresholds are chosen, indicating three regimes. Table 16 reports the summary of threshold specification

Table 16

Summary of Threshold Specification
Threshold variable: LRD4(-3) Estimated number of thresholds: 2 Method: Bai-Perron tests of L+1 vs. L sequentially determined thresholds Maximum number of thresholds: 3 Thresholds values estimated: -0.06234626, 0.0788706

When specifying the TAR model for D4 RIN prices, where the threshold variable is $dln(d6)_{t-3}$ the maximum number of thresholds is again set to 3, limiting the possibility to four regimes. Using the same Bai-Perron sequential method, the number of thresholds is found to be two, indicating a three regime TAR model. Table 8 reports the summary of threshold specification for the TAR model for D4 RIN prices.

Table 17

Summary of Threshold Specification
Threshold variable: LRD6(-3) Estimated number of thresholds: 2 Method: Bai-Perron tests of L+1 vs. L sequentially determined thresholds Maximum number of thresholds: 3 Thresholds values estimated: -0.007395268, 0.07113479

The next task is to determine whether the SETAR (3) or the TAR (3) model is a better fit for the D4 RIN series. To do so, each model is specified with the established delay parameters, and number of thresholds found in the threshold specifications. The model which minimizes the sum of squared residuals is deemed to be the best fitting model for D4 RINs.

Results indicate the SETAR with three regimes outperforms the TAR with three regimes. The SETAR (3) model results in a SSR of 1.896741, while the TAR (3) results in a SSR of 2.011920.

Table 15 reports the associated SSR for each model and Figure 6 depicts the sizable difference in associated sum of squared residuals for each model.

Table 18

Threshold Variable	SSR	Regimes
LRD4(-3)	1.896741	3
LRD6(-3)	2.011920	3

In the next section, the best fit models as determined by the above model selection procedures will be estimated.

The model of choice for D4 RINs is

$$\begin{aligned} Y_t = \{\beta_0 + & \left(X'\delta_1 + \beta_{p_1,1} Y_{t-p_1} + \varepsilon_t\right) I_1(Z_{t-d} < r_1) \\ & + \left(X'\delta_2 + \beta_{p_2,2} Y_{t-p_2} + \varepsilon_t\right) I_2(r_1 \le Z_{t-d} < r_2) \\ & + \left(X'\delta_3 + \beta_{p_3,3} Y_{t-p_3} + \varepsilon_t\right) I_3(r_2 \le Z_{t-d})\} \end{aligned}$$

$$X' = \text{vector of exogenous variables}$$

$$Z_{t-d} = \text{lagged values of log} - \text{differenced D4 RIN price}$$

$$r_j = \text{threshold values where } j = 1{:}\,2$$

$$I_m = \text{indicator variable equal to one if the argument is true, where } m = 1{:}\,3$$

$$\beta_0 = \text{intercept term assumed constant across regimes}$$

$$Y_{t-p_m} = \text{lagged dependent variables where } m = 1{:}\,3$$

The vector of exogenous variables includes biodiesel blend margins, D6 RIN price and end of week corn price. End of week corn prices are log-differenced to ensure stationarity, however biodiesel blend margins were found to be stationary without transformation.

6.5 Results of TAR estimation for D6 RIN series

Results indicate a presence of three regimes with three threshold values. The threshold values are estimated to be -0.2984065 and -0.21588. The threshold variable is the logarithmic value of weekly renewable volume obligations for ethanol blends. Therefore the threshold values represent the log of weekly ethanol quantities blended. The first regime includes 58 observations and occurs where $dln(rvo)_{t-2}$ is strictly less than -0.2984065. In this first regime, the lagged value of D6 RIN price is not statistically different from zero. The one explanatory variable which is highly significant is the price of biomass-based diesel D4 RINs. With a p-value of 0.0000 and a coefficient of 1.6879, the price of D6 RINs is strongly and positively correlated with D4 RINs. In this first regime, the ethanol blend margins are statistically significant at the 10 percent level and the coefficient is positive as expected, meaning that as the gap between gas price and ethanol price increases, so does the RIN price.

The second regime consists of 93 observations and is defined as those periods where the weekly ethanol blend quantities are greater than or equal to -0.2984065 and strictly less than -0.215888 or $-0.2984065 \leq dln(rvo)_{t-2} < -0.215888$. In this regime, only the lagged dependent variable of D6 RIN price is significant. With a p-value of 0.0001 and a coefficient of 0.542026, $dln(D6)_{t-1}$ is somewhat persistent.

In the third regime there are 117 observations and is defined as those periods where$-0.215888 \leq dln(rvo)_{t-2}$. In this regime, the lagged dependent variable is highly significant and positive with a p-value of 0.0061 and a coefficient of 0.262230. The only significant exogenous variable is D4 RIN price with a p-value of 0.0000 and a coefficient of 0.888960.

The intercept which was not specified to vary between regimes is not statistically different from zero with a p-value of 0.2902. Table 27 in the appendix reports the detailed results of the TAR model for D6 RIN series. Comparing the sum of squared residuals and the information criteria of to the linear model, the nonlinear TAR model with three regimes provides a better fit. Table 19 reports the R-squared, SSR and AIC for both the linear model and the TAR model and it appears the TAR model is superior to the linear specification.

Table 19

Linear model versus TAR model for D6 RIN price			
Linear Model		TAR (3) Model	
R-squared	0.139290	R-squared	0.297332
Sum squared resid	7.369559	Sum squared resid	5.798687
Akaike info criterion	-0.763609	Akaike info criterion	-0.898463

6.6 Results of SETAR estimation for D4 RIN series

An application of the SETAR model to D4 RIN series results in two thresholds with values of -0.06234626 and 0.0788706. Recall that the threshold variable chosen in this case is the third lag of log-differenced D4 RIN price. The first regime consists of 39 observations and is defined as the periods where the growth rate of D4 RIN price is strictly less than -0.06234626. During this period only the biodiesel blend margin and D6 RIN prices are statistically significant. The biodiesel blend margin is just significant at the 5 percent level with a p-value of 0.0521 and a positive coefficient of 0.059332, indicating the positive relationship between blend margins and RIN values as depicted in Figure 8 of section 5. Ethanol D6 RIN prices are highly significant with a p-value of 0.0004 and a coefficient of 0.375024, indicating the positive relationship between the two RIN prices.

The second regime consists of 177 observations and is defined as the periods where the growth rate of D4 RINs is greater than or equal to -0.06234626 and strictly less than 0.0788706 such that $-0.06234626 \leq dln(D6)_{t-3} < 0.0788706$. In this regime, the lagged value of the dependent variable is highly significant with a p-value of 0.0000 and a coefficient of 0.544318

The price of D6 ethanol RIN also has a statistically significant relationship with D4 RIN prices with a p-value of 0.0013. With a coefficient of 0.108048, D6 RINs are positively associated with

D4 RINs, which is also consistent with expectations. Due to the nested structure of RIN prices a negative relationship between the prices of any two RINs would be alarming and raise concerns to the model specification.

The third regime consists of 42 observations and is defined as those periods where the growth rate of D4 RINs is greater than or equal to 0.0788706 such that $0.0788706 \leq dln(D6)_{t-3}$. In this regime only the D6 RIN price is highly significant with a positive coefficient of 0.715988. The lagged value of D4 RIN price is significant at the 10 percent level with a p-value of 0.0856.

The intercept which is specified to be invariant among regimes is found to be statistically insignificant with a p-value of 0.1788. Table 28 in the appendix, reports the complete results of the SETAR model for D4 RIN price. Comparing the linear model of D4 RIN prices to the SETAR model shows that while the SETAR model does improve the SSR and R-squared, it also introduces enough added complexity that the AIC is not minimized in the SETAR model.

Table 20

Linear model versus SETAR model for D4 RIN price			
Linear Model		SETAR(3) Model	
R-squared	0.153066	R-squared	0.329722
Sum squared resid	1.924324	Sum squared resid	1.896741
Akaike info criterion	-2.080147	Akaike info criterion	-1.974170

Table 20 indicates, that while the SETAR model improves the goodness of fit over the linear model, the number of parameters added to the estimation also introduces substantial complexity. This is a drawback of the quick switching TAR and SETAR models. These models are essentially a piecewise linearization through the introduction of indicator variables that are equal to one if the threshold is crossed and zero if not, operating much like a light switch. In the next section, a smooth transition autoregressive (STAR) model is fitted to the data. In a STAR model, the switch from one regime to the next occurs through a smooth transition function of the threshold variable. The number of regimes will equal the number of unique values taken on by the transition function.

7. SMOOTH TRANSITION AUTOREGRESSIVE MODEL

The smooth transition autoregressive (STAR) model is represented by the equation

$$y_t = \boldsymbol{\alpha}'\boldsymbol{x}_t + \boldsymbol{\theta}'\boldsymbol{x}_t G(z_t; \gamma, c) + u_t$$

where, $\boldsymbol{x}_t = \left(1, y_{t-1}, \dots y_{t-p};\ x_{1t}, \dots, x_{kt}\right)'$, $\boldsymbol{\alpha} = (\alpha_0, \alpha_1, \dots \alpha_m)'$, $\boldsymbol{\theta} = (\theta_0, \boldsymbol{\theta}_1') = (\theta_0, \theta_1, \dots \theta_m)$ and $u_t \sim i.i.d(0, \sigma^2)$. The function $G(z_t; \gamma, c)$, identifies transition thresholds, z_t is a transition variable, γ and c are slope and location parameters respectively. The transition function is a continuous function between zero and unity, assumed to take a logistic form of $G(z_t; \gamma, c) = [1 + \exp\{-\gamma(z_t - c)\}]^{-1}$ so that the model is also known as the logistic STAR or LSTAR. As z_t increases, the logistic function changes monotonically from zero to unity. The STAR model with a logistic transition function is a regime switching model, where the transition from one regime to the next is smooth, and the regime that occurs at time t is determined by z_t.

7.1 Linearity testing against the LSTAR model

Given a specific nonlinear alternative to the linear model, Lagrange Multiplier tests can be calculated which are optimal in terms of power against that nonlinearity (Granger & Terasvirta, 1993). The following steps can be taken to calculate these LM type tests.

1. Regress y_t on x_t and compute the residuals $\hat{u}_t = y_t - a'x_t$ and $SSR_0 = \sum \hat{u}_t^2$

2. If the transition variable is known to be z_{td} compute the auxiliary regression of $\hat{u}_t = \beta' \boldsymbol{x}_t + \sum_{j=1}^{m} (\varphi_{dj} z_{td} x_{tj} + \psi_{dj} z_{td}^2 x_{tj} + \kappa_{dj} z_{td}^3 x_{tj}) + v_t$ and obtain the SSR
3. Calculate the statistic $LM = \frac{T(SSR_0 - SSR)}{SSR_0}$

The null hypothesis is thus $\varphi_{dj} = \psi_{dj} = \kappa_{dj} = 0$ and the LM statistic has an asymptotic $\chi^2(3m)$ where m is the number of parameters.

Performing the above test on D6 and D4 RIN series, results in LM-test statistics of 78.465 and 51.015 respectively for p-values of 0.0000 in both cases, rejecting the null hypothesis of linearity against the alternative LSTAR nonlinear model.

7.2 Testing the significance of the transition variable

A form of the auxiliary regression used in testing for linearity may be used to select the best transition variable.

$$\hat{u}_t = \beta_0' x_t + \beta_1' x_t z_{td} + \beta_2' x_t z_{td}^2 + \beta_3' x_t z_{td}^3 + \eta_t$$

When the correct transition variable is selected the auxiliary regression is indeed the appropriately specified auxiliary regression against the true nonlinear alternative. An incorrect transition variable would render it misspecified (Granger & Terasvirta, 1993). If linearity is rejected for several candidate transition variables, then the transition variable with the smallest p-value or the largest test statistic is selected. In this procedure the same candidate transition variables used in TAR and SETAR models are considered here for the STAR models. Namely this includes the log of weekly renewable volume obligations (LRVO), and lagged values of D6 and D4 RIN price.

Table 21: Test for most significant D6 transition variable

Transition variable tests for D6 RINs
H0: The transition variable is not significant

Transition variable (STR)	F-statistic	P-value	Transition variable (STR)	F-statistic	P-value
LRVO(-1)	121.034	0.000	LRD6(-1)	38.892	0.000
LRVO(-2)	50.166	0.000	LRD6(-2)	48.172	0.000
LRVO(-3)	29.371	0.000	LRD6(-3)	80.889	0.000
LRVO(-4)	69.877	0.000	LRD6(-4)	43.491	0.000
LRVO(-5)	119.244	0.000	LRD6(-5)	54.027	0.000

Table 21, indicates the weekly renewable volume obligations is a more appropriate transition variable than lagged values of D6 RINs. Weekly RVO's with a delay parameter of 1st lag and 5th lag have the highest test statistic by a large margin, so these two delay parameters are utilized in the STAR estimation of D6 RINs.

Table 22: Test for most significant D4 transition variable

Transition variable tests for D4 RINs
H0: The transition variable is not significant

Transition variable (STR)	F-statistic	P-value	Transition variable (STR)	F-statistic	P-value
LRD4(-1)	70.812	0.000	LRD6(-1)	11.304	0.000
LRD4(-2)	58.150	0.000	LRD6(-2)	21.374	0.000
LRD4(-3)	92.631	0.000	LRD6(-3)	14.816	0.000
LRD4(-4)	37.584	0.000	LRD6(-4)	28.587	0.000
LRD4(-5)	17.819	0.000	LRD6(-5)	27.713	0.000

Table 22, indicates that endogenous lagged dependent variables are the most appropriate transition variables for D4 RIN prices as evidenced by the larger test statistics. Delay parameters of the 1st lag and 3rd appear to be the best fitting transition variables for D4 RINs and these will be utilized in the estimation of the D4 STAR model.

7.3 Estimation of the STAR Model

Estimation is performed with non-linear least squares using a Gauss-Newton optimization procedure with Marquardt iteration steps. The log-likelihood function is constructed under the assumption of normality and is thus represented as

$$\ln(l) = -\frac{1}{2}\ln(2\pi) - \ln(\sigma) - \frac{1}{2}\left(\frac{y_t - \boldsymbol{\alpha}'\boldsymbol{x}_t - \boldsymbol{\theta}'\boldsymbol{x}_t G(z_t;\gamma,c)}{\sigma}\right)^2$$

In the LSTAR model, the function $G(z_t;\gamma,c)$ is normalized in the exponential function by the standard deviation of the transition variable $\hat{\sigma}(z_t)$. Doing so rescales the slope parameter of the transition function γ since its value could be much larger than other parameters. To be clear the transition function takes the form

$$G(s_t;\gamma,c) = \ [1 + \exp\{-\gamma(z_t - c)/\hat{\sigma}(z_t)\}]^{-1}\,.$$

Based on Table 21, the LSTAR is estimated for D6 RIN price while specifying the first lag of weekly renewable volume obligations. Starting values for the optimization procedure are chosen randomly using a normal random number generator which generates a vector of starting values using a random draw from a normal distribution with a mean of zero and variance on unity. The model is specified with the same explanatory variables as the linear and TAR models so that a direct comparison of goodness of fit can be made.

Newey-West Heteroskedastic and autocorrelation corrected (HAC) standard errors are estimated to correct for any possible serial correlation and heteroskedasticity. Recall that serial correlation of the second-order was found in the case of the linear model. Although residual outliers are suspected of triggering this result, HAC standard errors are estimated in an attempt to make inference more reliable.

Table 23: D6 STAR estimation

Dependent Variable: LRD6
Method: Least Squares (Gauss-Newton / Marquardt steps)
Included observations: 269 after adjustments
HAC standard errors & covariance using observed Hessian (Bartlett kernel,
Newey-West fixed bandwidth = 5.0000)
LRD6=C(1)+C(2)*LRD6(-1)+C(3)*ETHMRGN+C(4)*DLCORN+C(5)*LRD4
+(C(6)+C(7)*LRD6(-1)+C(8)*ETHMRGN+C(9)*DLCORN+C(10)*LRD4)
/(1+@EXP(-C(11)*(LRVO(-1)-C(12))/0.185725335183854))

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.023274	0.010950	2.125594	0.0345
LRD6(-1)	0.127293	0.073590	1.729756	0.0849
ETHMRGN	0.045740	0.017859	2.561260	0.0110
DLCORN	-0.213122	0.200608	-1.062382	0.2891
LRD4	0.492432	0.150171	3.279134	0.0012
C(2)	4.467668	0.995157	4.489411	0.0000
LRD6(-1)’	11.58177	2.571800	4.503371	0.0000
ETHMRGN’	6.991539	1.462763	4.779679	0.0000
DLCORN’	27.75939	4.042605	6.866709	0.0000
LRD4’	8.492061	1.257257	6.754433	0.0000
GAMMA	-405.7669	55.20474	-7.350219	0.0000
THRESHOLD	-0.374341	8.51E-05	-4399.660	0.0000

R-squared	0.513805	Mean dependent var	0.011282
Adjusted R-squared	0.492996	S.D. dependent var	0.175581
S.E. of regression	0.125021	Akaike info criterion	-1.277084
Sum squared resid	4.016981	Schwarz criterion	-1.116726
Log likelihood	183.7678	Hannan-Quinn criter.	-1.212684
F-statistic	24.69045	Durbin-Watson stat	1.625610
Prob(F-statistic)	0.000000		

Table 23 reports the estimation results of the D6 STAR model. A large value for the smoothness parameter $\hat{\gamma}$ indicates the regime switch may be a quick transition rather than a smooth one. However, large values of $\hat{\gamma}$ are not of significant concern. As $\hat{\gamma} \to \infty$ the transition function $G(s_t; \gamma, c)$ becomes steeper which means the transition is faster. The threshold variable $\hat{c}$ is estimated to be -0.374341 which is within the range of the transition variable $\ln(rvo)_{t-1}$.

Figure 11: Evaluation of D6 Transition Function

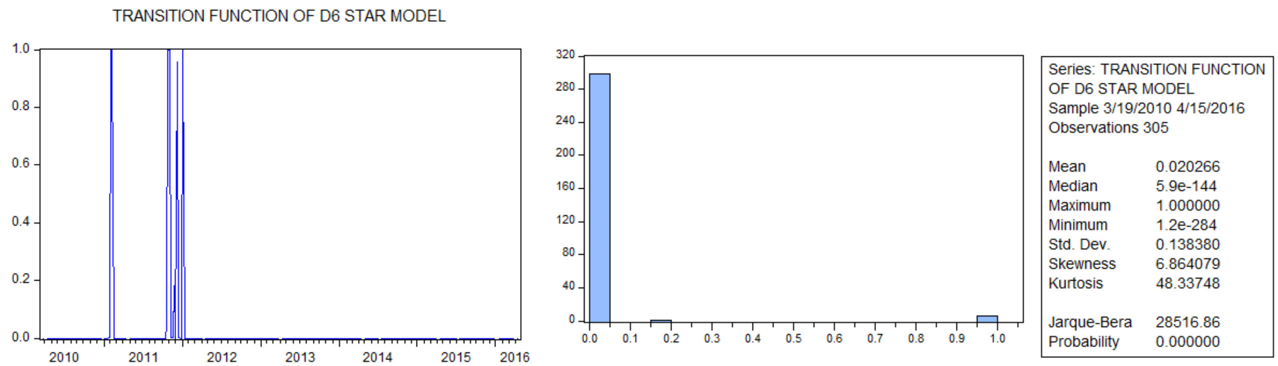


Figure 11 indicates the transition function for D6 RINs takes on only three values and is largely clustered around zero. This would indicate the transition between regimes is not smooth, but occurs rapidly much like a TAR model. Initially this might provide evidence that the TAR model estimated in section 8 is the more appropriate model. To compare the overall goodness of fit between the D6 TAR model and the D6 STAR model, the SSR, R-squared and AIC are evaluated.

Table 24: D6 Model Comparison

Linear model versus TAR and STAR model for D6 RIN price					
Linear Model		TAR (3)		STAR	
R-squared	0.139290	R-squared	0.297332	R-squared	0.513805
SSR	7.369559	SSR	5.798687	SSR	4.016981
AIC	-0.763609	AIC	-0.898463	AIC	-1.277084

Table 24, indicates that the STAR model provides the best fit for D6 RIN prices. Both the SSR and the AIC are improved by large margins, and the R-squared is nearly twice as large as the TAR model.

Estimating the STAR model for D4 RINs is carried out in a similar fashion. As indicated by Table 22 the transition variable chosen for D4 RINs is the third lag of D4 RINs.

Table 25: D4 STAR estimation

Dependent Variable: LRD4
Method: Least Squares (Gauss-Newton / Marquardt steps)
Included observations: 252 after adjustments
HAC standard errors & covariance using observed Hessian (Bartlett kernel,
Newey-West fixed bandwidth = 5.0000)
LRD4=C(1)+C(2)*LRD4(-1)+C(3)*BDMRGN+C(4)*DLSOY+C(5)*LRD6
+(C(6)+C(7)*LRD4(-1)+C(8)*BDMRGN+C(9)*DLSOY+C(10)*LRD6)/(1
+@EXP(-C(11)*(LRD4(-3)-C(12))/0.0888091548199191))

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.001065	0.020869	-0.051028	0.9593
LRD4(-1)	0.350813	0.106685	3.288297	0.0012
BDMRGN	0.000756	0.024364	0.031040	0.9753
DLSOY	-0.032501	0.154418	-0.210477	0.8335
LRD6	0.147205	0.040533	3.631694	0.0003
C(2)	-0.050522	0.027390	-1.844576	0.0663
LRD4(-1)’	-0.465275	0.148342	-3.136511	0.0019
BDMRGN’	0.161773	0.041676	3.881660	0.0001
DLSOY’	-2.192636	0.572821	-3.827787	0.0002
LRD6’	0.619476	0.136913	4.524608	0.0000
GAMMA	-40.55228	142.7554	-0.284068	0.7766
THRESHOLD	-0.107872	0.016007	-6.739126	0.0000

R-squared	0.293940	Mean dependent var	0.005438
Adjusted R-squared	0.261579	S.D. dependent var	0.093707
S.E. of regression	0.080524	Akaike info criterion	-2.154085
Sum squared resid	1.556172	Schwarz criterion	-1.986017
Log likelihood	283.4147	Hannan-Quinn criter.	-2.086458
F-statistic	9.083128	Durbin-Watson stat	1.620708
Prob(F-statistic)	0.000000		

Table 25 reports the estimation of D4 STAR model. Similar the D6 STAR model the estimated value of $\hat{\gamma}$ is large and indicates the regime switch occurs quickly. The threshold variable $\hat{c}$ is estimated to be -0.107872 which is within the range of the transition variable $ln\Delta D4_{t-3}$. To evaluate the transition function and determine if the regime switch occurs smoothly or rapidly, the values of the transition function are plotted.

Figure 12: Evaluation of D4 Transition Function

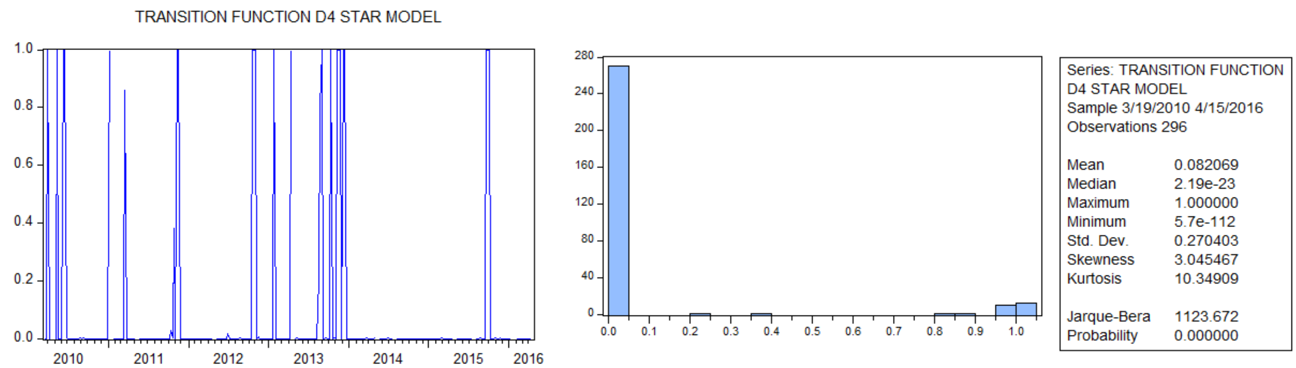


Figure 12, indicates the transition function for D4 STAR model does not take on many values and the regime changes occur rapidly as opposed to smoothly. However, to determine the goodness of fit, the R-squared, SSR and AIC are compared.

Table 26: D4 Model Comparison

Linear model versus SETAR and STAR model for D4 RIN price					
Linear Model		SETAR (3)		STAR	
R-squared	0.153066	R-squared	0.329722	R-squared	0.293940
SSR	1.924324	SSR	1.896741	SSR	1.556172
AIC	-2.080147	AIC	-1.974170	AIC	-2.154085

Table 26 indicates the STAR model outperforms both the SETAR model and the linear model in regards to minimizing the SSR and AIC. The SETAR model has a larger R-squared than the

STAR model, but in choosing the best fitting model, the minimized criteria of SSR and AIC trump the smaller R-squared.

8. CONCLUSION

The market for renewable identification numbers (RINs) is complex and constantly evolving. Understanding the behavior of the RINs can provide important insights into an industry which may be critical to long tem energy independence. Federal regulation which determines annual renewable volume obligations is often uncertain year to year, causing market participants, obligated parties and other agents to adapt their behaviors to the changing regulations. It is the behavior of these agents which is reflected in the multiple regimes and structural breaks of the RIN price.

Nonlinearities in the RIN market are examined by fitting threshold autoregressive and smooth transition autoregressive models to historical RIN data. Theoretical RIN price is primarily driven by the core value of the RIN which is determined by the gap between the price of the biofuel and conventional fuel, also known as the blend margin. Therefore, ethanol and biodiesel blend margin variables are introduced as exogenous variables and thought to be primary determinants of RIN price. The cost of corn and soybeans are also included in the model as they're thought to influence the price at which the biofuels are supplied.

RIN prices are found to exhibit significant nonlinearity and regime change. The regime change is found to occur quickly as opposed to smoothly over time. However, the smooth transition autoregressive (STAR) model is found to be the best fit. STAR models are capable of taking on smooth transitions and quick abrupt transitions, making them well suited to model RIN prices.

It is believed that coupling patterns observed in the RIN market are brought about by some proximity to the ethanol blend wall. In other words, there is some unobservable threshold, that when crossed, brings about a change in the behavior of the RIN market. Therefore a key variable in this paper is weekly renewable volume obligations for producers and importers of gasoline. Weekly renewable volume obligations are found to be the most significant transition variable for D6 RIN price regime changes. In regards to D4 RIN prices, past values of D4 RIN price are found to be the most significant variable in determining regime change. This is in line with expectations. The ethanol blend wall represents a real challenge to producers and importers which are obligated to meet annual blend mandates. Therefore, obligated parties are over complying with the biodiesel mandate in order to generate D4 biodiesel RINs which can be submitted for compliance with the ethanol mandate.

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APPENDIX

Table 27: TAR estimation results for D6 RINs

Dependent Variable: LRD6
Method: Threshold Regression
Included observations: 268 after adjustments
Threshold type: Bai-Perron tests of L+1 vs. L sequentially determined thresholds
Threshold variables considered: LRD6(-2) LRVO(-2)
Threshold variable chosen: LRVO(-2)
Threshold selection: Trimming 0.15, Max. thresholds 3, Sig. level 0.05
Threshold values used: -0.2984065, -0.215888

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LRVO(-2) < -0.2984065 -- 58 obs				
LRD6(-1)	-0.018821	0.062136	-0.302900	0.7622
ETHMRGN	0.072367	0.038806	1.864852	0.0634
DLCORN	0.346328	0.430657	0.804184	0.4220
LRD4	1.687900	0.301359	5.600962	0.0000
-0.2984065 <= LRVO(-2) < -0.215888 -- 93 obs				
LRD6(-1)	0.542026	0.133448	4.061714	0.0001
ETHMRGN	-0.006226	0.030661	-0.203074	0.8392
DLCORN	-0.613931	0.381963	-1.607305	0.1092
LRD4	-0.057746	0.162934	-0.354416	0.7233
-0.215888 <= LRVO(-2) -- 117 obs				
LRD6(-1)	0.262230	0.094836	2.765082	0.0061
ETHMRGN	0.035021	0.038309	0.914157	0.3615
DLCORN	0.213230	0.317800	0.670957	0.5029
LRD4	0.888960	0.149973	5.927472	0.0000
Non-Threshold Variables				
C	0.014854	0.014016	1.059802	0.2902

R-squared	0.297332	Mean dependent var	0.011649
Adjusted R-squared	0.264265	S.D. dependent var	0.175806
S.E. of regression	0.150798	Akaike info criterion	-0.898463
Sum squared resid	5.798687	Schwarz criterion	-0.724274
Log likelihood	133.3941	Hannan-Quinn criter.	-0.828501
F-statistic	8.991887	Durbin-Watson stat	1.898439
Prob(F-statistic)	0.000000		

Table 28: SETAR estimation results for D4 RINs

Dependent Variable: LRD4
Method: Threshold Regression
Included observations: 258 after adjustments
Threshold type: Bai-Perron tests of L+1 vs. L sequentially determined thresholds
Threshold variables considered: LRD4(-3) LRD6(-3)
Threshold variable chosen: LRD4(-3)
Threshold selection: Trimming 0.15, Max. thresholds 3, Sig. level 0.05
Threshold values used: -0.06234626, 0.0788706

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LRD4(-3) < -0.06234626 -- 39 obs				
LRD4(-1)	0.084483	0.099846	0.846134	0.3983
BDMRGN	0.059332	0.030396	1.951986	0.0521
DLSOY	-0.910617	0.658333	-1.383216	0.1679
LRD6	0.375024	0.104542	3.587308	0.0004
-0.06234626 <= LRD4(-3) < 0.0788706 -- 177 obs				
LRD4(-1)	0.544318	0.091176	5.969974	0.0000
BDMRGN	0.023248	0.020093	1.156983	0.2484
DLSOY	-0.046817	0.179469	-0.260863	0.7944
LRD6	0.108048	0.033272	3.247400	0.0013
0.0788706 <= LRD4(-3) -- 42 obs				
LRD4(-1)	0.173871	0.100721	1.726261	0.0856
BDMRGN	0.023698	0.028186	0.840743	0.4013
DLSOY	0.700899	0.477459	1.467977	0.1434
LRD6	0.715988	0.098420	7.274821	0.0000
Non-Threshold Variables				
C	-0.021219	0.015736	-1.348430	0.1788

R-squared	0.329722	Mean dependent var	0.005733
Adjusted R-squared	0.296892	S.D. dependent var	0.104933
S.E. of regression	0.087988	Akaike info criterion	-1.974170
Sum squared resid	1.896741	Schwarz criterion	-1.795145
Log likelihood	267.6679	Hannan-Quinn criter.	-1.902183
F-statistic	10.04334	Durbin-Watson stat	1.926641
Prob(F-statistic)	0.000000		