Revisiting Biodiesel Hedging

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Abstract

Previous research found that both soybean oil and heating oil futures should be used to hedge biodiesel price risk. This was sensible because blending mandates caused biodiesel prices to be driven by that of its primary input—soybean oil. Much has changed in recent years, with plummeting demand during the COVID pandemic, biodiesel plants struggling to break-even in 2020, and then incurring losses in 2021 as soybean oil prices skyrocketed with the rise of renewable diesel—a relatively new biomass-based diesel fuel in high demand largely due to green policies in California. This study revisits the appropriate strategies for hedging biodiesel production risk and finds that soybean oil has become a less important hedging vehicle.

Keywords: biodiesel, composite hedge, cross-hedge, encompassing, hedging effectiveness

JEL Classification: Q420, Q410, Q480, Q160, Q110, Q130

Introduction

Biofuels are an increasingly important component of the energy industry, and production of biofuels and their byproducts entails exposure to substantial price risk. Accordingly, scholars investigate methods to hedge price risk for corn ethanol (Dahlgran, 2009; Franken & Parcell, 2003), its byproduct—dried distillers grains (DDGs)—a livestock feed (Brinker, Parcell, Dhuyvetter, & Franken, 2009), and soybean oil and poultry fat inputs to biodiesel production Graf, McKenzie, and Popp (2008). Most recently, Franken, Irwin, and Garcia (2021) show that binding blending mandates imply that biodiesel hedges should include positions in the futures market for its primary input, soybean oil, in addition to conventionally used heating oil/diesel futures.[1] As shown in Figure 1, mandating that a certain amount of biodiesel ($Q2^M$) be blended with conventional ultra-low sulfur diesel causes biodiesel prices to be driven by shifts in its

[1] The heating oil futures contract transitioned to an ultra-low sulfur diesel fuel (ULSD) futures contract in May 2013, prior to the period of analysis; hence we use the term diesel futures but also use the contract abbreviation/symbol HO in use by the CME Group futures exchange.

supply (i.e., from $Supply_1$ to $Supply_2$ or $Supply_3$), and thus, the cost of soybean oil which is the largest input cost. This is consistent with Irwin's (2015) finding that the soybean oil prices Granger cause biodiesel prices but not the reverse.

However, the effectiveness of a given futures contract and hedge ratio may vary with changes in numerous economic factors across time (Haigh & Holt, 2000; Hauser, Garcia, & Tumblin, 1990; Mattos, Garcia, Leuthold, & Hahn, 2003; Pennings & Meulenberg, 1997a). Much has changed since early 2020, when Franken, Irwin, and Garcia's (2021) sample period ended. With plummeting demand during the COVID pandemic, traditional FAME (fatty acid methyl ester) biodiesel plants struggled to break-even in 2020, and experienced major losses in 2021, as soybean oil prices skyrocketed with the rise of renewable (or green) diesel—a relatively new "drop-in" biomass-based diesel fuel. It is in high demand largely due to the Low Carbon Fuel Standard policy in California. As shown in Figure 2, FAME biodiesel production has grown substantially over the last two decades, while renewable diesel production was essentially nonexistent prior to 2011, and has taken off recently. Corresponding increases in demand for, and hence, prices of soybean oil, particularly since 2021, raised its share of the value of the soybean crush to nearly on par with that of soybean meal, whereas soybean oil and meal comprised about a third and two thirds of the crush's value, respectively, for much of the prior decade (Figure 3).

In light of these changed conditions, this study revisits the appropriate hedging strategies for FAME biodiesel price risk. Sanders and Manfredo's (2004) encompassing framework is used to assess cross-hedge relationships between four biodiesel spot markets and heating oil/diesel futures and soybean oil futures over a four-week hedging horizon. The advantage of this approach over others is that it permits testing the statistical significance of differences in hedging effectiveness of alternative futures contracts to determine if a particular contract encompasses the risk-reduction properties of another contract, or if using the competing contracts in a composite hedge more effectively minimizes residual basis risk.[2] The analysis focuses on weekly observations over February 14, 2020 through September 2, 2022, a period of tumultuous change in biodiesel markets.

Data

Weekly data on spot prices for biodiesel and futures prices for soybean oil and heating oil/ultra low sulfur diesel are available from January 26, 2007 through September 2, 2022 (Figure 4). Iowa biodiesel prices on Fridays are reported by the US Department of Agriculture (USDA). Biodiesel prices for Chicago, New York, and the Gulf of Mexico are available on Thursdays from the Oil Price Information Service (OPIS). Spot price series for the Gulf of Mexico and New York, respectively, start on February 23, 2007 and October 12, 2012. Nearby close of day futures prices, rolled over on the first day of contract maturity, are obtained from Barchart.com on

[2] While several measures of hedging effectiveness exist (Pennings & Meulenberg, 1997b list frequently used measures), the concept has not changed dramatically since Ederington's (1979) initial use of the correlation coefficient to measure the relationship between changes in cash and futures prices (Sanders & Manfredo, 2004). Myers and Thompson (1989) suggest that conditioning hedging rules on all available information (e.g., past prices) improves upon the effectiveness of unconditional hedges, but also acknowledge that conditional hedge ratios closely approximate unconditional hedge ratios estimated with price changes. Moreover, conclusions about hedging performance vary little with the chosen measure (Floros & Vougas, 2006).

Thursdays and Fridays corresponding to the cash price series. As Franken, Irwin, and Garcia's (2021) analysis of biodiesel hedging covers January 26, 2007 through February 7, 2020, the analysis presented here focuses on February 14, 2020 through September 2, 2022.

Biodiesel prices at each location trade at similar levels and patterns over the study period (Figure 4). Biodiesel prices for the period of analysis also exhibit similar means, ranging from \$4.77/gallon (gal) in Iowa to \$4.99/gal in New York (Table 1), which is notably higher than means of around \$3.60/gal for the period analyzed by Franken et al. (2021). The Chicago and Gulf markets exhibit similar levels of price volatility, as indicated by standard deviations and maximum and minimum statistics, with New York and Iowa exhibiting somewhat higher and lower volatility, respectively. In comparison, the heating oil/diesel futures price exhibits a lower average of \$2.16/gal and less variability, while the soybean oil futures price averages about ¢52/pound (lb) or equivalently \$52/hundredweight (cwt). Franken et al. (2021) report higher heating oil/diesel futures (\$2.25/gal) and lower soybean oil futures (¢39.40/lb) on average. Prior to the hedging analysis, soybean oil futures prices are converted from cents per pound to dollars per gallon, consistent with the pricing of heating oil futures and biodiesel (e.g., ¢52.00/lb × 7.55 lb/gal ÷ 100¢/\$ = \$3.93/gal).

Correlations are presented in Table 2. The lowest correlation among the spot prices is 0.98 between Iowa and New York, which again attests to how similar the series are. Spot biodiesel prices are slightly more correlated with soybean oil futures than heating oil/diesel futures, but no longer to the degree Franken et al. (2021) report (>0.90 with soybean oil futures and >0.72 with heating oil/diesel futures), which suggests the hedging weight that the prior study found should be placed on soybean oil futures could potentially be in decline.

As noted above, Irwin (2015) previously found that the soybean oil prices Granger cause biodiesel prices but not the reverse. For comparison, Table 3 presents tests of the null hypothesis that a particular price series does not Granger cause another price series for the period covered by Franken, Irwin, and Garcia's (2021) initial hedging study and for the time since. In particular, biodiesel prices are paired with either heating oil or soybean oil futures prices in the analysis. For the recent time period, the null hypothesis can be rejected at the one percent level for every price pair considered, implying that both futures prices Granger cause biodiesel prices in each location and vice versa. Results for the earlier period also seem to contrast Irwin's (2015) finding, given that biodiesel prices tend to Granger cause soybean oil (and heating oil) futures more so than the reverse. Also, other than in Iowa, the null hypothesis that biodiesel prices did not Granger cause heating oil futures prices could not be rejected at conventional levels for the earlier period. In fact, previously, there was no Granger causation between heating oil futures and Chicago or the Gulf, but biodiesel prices in all locations Granger-caused soybean oil futures. What is clear is that there appears to be changes in the causal relationships among these price series that could potentially affect the effectiveness of the hedging approach advocated by the prior study.

As expected, Augmented Dickey-Fuller (ADF) tests are unable to reject the null hypothesis of nonstationarity for each of the data series at conventional levels (Table 4). Differencing the data yields stationary series, and is consistent with the empirical approach outlined below.

Empirical Methods and Procedures

Leuthold, Junkus, and Cordier (1989) state that ex-post minimum variance hedge ratios are commonly estimated with ordinary least squares regression as

$$\Delta CP_t = \alpha + \beta \Delta FP_t + e_t, \qquad (1)$$

where Δ represents changes in cash prices CP_t and futures prices FP_t, α is the trend in cash prices, β is the ex-post minimum variance hedge ratio, and e_t is residual basis risk.[3]

Following Sanders and Manfredo (2004), the standard minimum variance regression can be used to identify the relative hedging effectiveness of two competing contracts and/or their combination. Equations (2) and (3) respectively represent hedging with the incumbent or original contract (e.g., heating oil/diesel futures) and an alternative or competing contract (e.g., soybean oil futures).

$$\Delta CP_t = \alpha_0 + \beta_0 \Delta FP_t^{0} + e_{0,t}, \qquad (2)$$

$$\Delta CP_t = \alpha_1 + \beta_1 \Delta FP_t^{1} + e_{1,t}. \qquad (3)$$

As in Harvey, Leybourne, and Newbold's (1998) regression test of forecast encompassing, a modified version of the *J*-test of nonnested hypotheses (Maddala, 1992) enables testing the null hypothesis that the incumbent contract *encompasses* the proposed alternative contract. Fitted values from equations (2) and (3), represented by y_0 and y_1, respectively, and actual values of the dependent variable, represented by y, can be inserted into equation (4):

$$y - y_0 = \Phi + \lambda(y_1 - y_0) + v. \qquad (4)$$

The $y - y_0$ term is the residual basis or spread risk of the first model, and $y_1 - y_0$ is the difference in fitted values of the two models. Here, we are not concerned with conventional basis

[3] Despite dispute over whether such models should be estimated in price levels, price changes, or percentage changes, the price change formulation in equation (1) is a common approach to estimating unconditional hedge ratios.

but rather the spread in the case of a cross hedge. In this case, if λ is not statistically different from zero, then the second model has no more explanatory power than the first. Therefore, if $\lambda = 0$, the new contract does not provide a reduced basis or spread risk above the original contract. Following Granger and Newbold (2014), adding λy to each side of equation (4), simplifying, and substituting for $y - y_0$ and $y - y_1$ with the corresponding residual errors e_0 and e_1 from the ordinary least squares (OLS) regressions of equations (2) and (3) yields:

$$e_{0,t} = \Phi + \lambda[(e_{0,t} - e_{1,t})] + v_t. \tag{5}$$

Equation (5) is similar to Harvey, Leybourne, and Newbold's (1998) regression test for forecast encompassing. Here, λ is the weight to be placed on the new futures contract and $(1- \lambda)$ is the weight to be placed on the original contract. A two-tailed test of the null hypothesis that the incumbent encompasses the alternative (i.e., $\lambda = 0$) reveals the relative effectiveness of the proposed hedges in terms of residual basis risk.[4] Below are the alternative potential results in a hedging context.

$\lambda = 0$: All hedging should be in the original, incumbent futures market.

$0 < \lambda < 1$: A combination of hedging should be done in each market with λ as the weight assigned to the new futures contract.

$\lambda = 1$: All hedging should be done in the alternative, competing futures market.

As shown by Maddala (1992), the λ that best reduces error or risk can be illustrated as:

[4] Harvey, Leybourne, and Newbold (1998) suggest a one-tailed test in the context of a composite forecast. In a hedging context, the possibility of negative hedge ratios (Anderson & Danthine, 1981) makes a two-tailed test more appropriate.

$$\lambda = \frac{\sigma^2 e_0 - \rho e_0 e_1}{\sigma^2 e_0 + \sigma^2 e_1 - 2\rho e_0 e_1 \sigma e_0 \sigma e_1}, \tag{6}$$

where, σ^2, σ, and ρ represent the variance, standard deviation, and correlation concerning basis risk for the original and new models. Maddala (1992) also shows:

$$\lambda \geq 0 \ \text{ iff } \ \frac{\sigma e_0}{\sigma e_1} \geq \rho e_0 e_1, \text{ and} \tag{7}$$

$$\lambda < 0 \ \text{ iff } \ \frac{\sigma e_0}{\sigma e_1} < \rho e_0 e_1. \tag{8}$$

The λ in equations (3b) and (3c) show the ability of the new futures contract to reduce the residual basis risk associated with the original futures contract.

Myers and Thompson (1989) argue that the appropriately specified hedging rule is conditioned on all available information (e.g., lagged or past prices). Sanders and Manfredo's (2004) approach is applicable to alternative specifications, including conditional hedging regressions. Hence, the appropriate hedging model is investigated, including lag structure and whether paired price series are cointegrated such that a long-run equilibrium relationship exists and inclusion or an error correction term is appropriate. In the interest of space, general findings of this analysis are described below with further details available from the authors upon request.

As noted, ADF tests fail to reject the null hypothesis of a unit root for the data in levels (i.e., nonstationarity) but do reject it using first-differenced data (i.e., stationarity), meaning that long-run equilibrium relationships may be estimated (Table 4). The well-known test for cointegration attributed to Engle and Granger (1987) applies the ADF test of stationarity to the error term from an OLS regression of two individual nonstationary price series (Table 5). Finding a (non)stationary error term means the two series are (not) cointegrated. Whereas this test returned relatively greater evidence of cointegration of biodiesel prices with soybean oil futures than with heating oil/diesel futures in the period covered by Franken, Irwin, and Garcia (2021), the reverse now appears to be the case. Soybean oil futures are no longer cointegrated with biodiesel prices other than in Iowa, which exhibits similar evidence of cointegration with both futures contracts. Specifically, ADF test statistics exceed the five percent critical value, indicating stationarity of the error term, and hence, cointegration of Iowa biodiesel price with both futures contracts. All three other biodiesel markets are cointegrated with heating oil/diesel futures prices at the one percent level but cannot be said to evidence cointegration with soybean oil futures at any conventional level.

Multivariate tests of cointegration commonly employ the Johansen (1988) method, which utilizes trace tests to investigate the number of cointegrating vectors (Table 6). The null hypothesis is that there are no more than *r* cointegrating vectors with the alternative hypothesis that there exist more than *r* cointegration vectors. Like the ADF tests of stationarity of residuals, the trace test results were somewhat more supportive of cointegration of biodiesel prices with soybean oil futures than with heating oil/diesel futures in the period covered by Franken, Irwin, and Garcia (2021) but now offer little evidence of cointegration for any of the price pairs considered. Research has identified difficulties with testing for unit roots in the presence of cointegration (Mallory & Lence, 2012; Reed & Smith, 2017) that may apply to the results obtained here. Here, we follow a straightforward and conservative path. Allowing for the possibility of cointegration, we proceed below with results of error correction models with various lag structures chosen by minimizing SIC (Table 7). The approach is consistent with Hassouneh et al.'s (2012) use of error correction models in the presence of long-run relationships between biodiesel and input prices in Spain. Furthermore, it facilitates comparison with Franken, Irwin, and Garcia's (2021) hedging analysis. To assess the sensitivity of estimates to model specification, results of error correction model results are compared with those of GARCH(1,1) models known for their robust nature (Hansen & Lunde, 2005).

Results

Table 8 contains selected regression results derived from error correction models using a four week hedging horizon.[5] Recall that prior to regression analysis, soybean oil futures prices are converted from cents per pound to dollars per gallon, consistent with the pricing of heating oil futures and biodiesel. The estimated hedge ratio β is obtained from estimating the hedging regressions for the incumbent futures contract (i.e., heating oil/diesel) and alternative or competing futures contract (i.e., soybean oil futures) given in equations 2 and 3. Taking Iowa as an example (Table 8), the heating oil and soybean oil hedge ratios of 0.45 and 0.58 are the ratios of heating oil-to-biodiesel and soybean oil-to-biodiesel, respectively. That is, for separate hedges, 0.45 gal of heating oil or 4.38 lb (= 0.58 gal × 7.55 lb/gal) of soybean oil is required to hedge each gallon of biodiesel. Relative to other locations, the hedge ratios for the two futures contracts are closer in magnitude in the production region of Iowa, with slightly more weight placed on the futures for the biodiesel feedstock—soybean oil. This is because the hedge ratio for heating oil is consistently higher in the other demand-oriented locations, while hedge ratio for

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[5] That is, four-week price differences represent a four-week hedging horizon. Franken, Irwin, and Garcia (2021) also consider eight- and 24-week price differences, representing eight- and 24-week hedging horizons and report that they yield qualitatively similar results, as do GARCH(1,1) models, that we also consider due to their robust nature (Hansen & Lunde, 2005).

soybean oil is fairly consistent across all locations. Hedge ratios for both contracts were lower in Iowa than in other locations in Franken, Irwin, and Garcia's (2021) results.

The estimated hedging weight λ for the alternative futures contract (i.e., soybean oil futures) is obtained from estimating the encompassing regression given in equation 5, with the remainder (1-λ) being the weight to be placed on the incumbent futures contract (i.e., heating oil futures). Like in Franken, Irwin, and Garcia (2021), the results in Table 8 still indicate that substantial hedging weight should be placed on the soybean oil futures contract with the highest weights for soybean oil found for Iowa (0.90) and the lowest for New York (0.31). While this same general pattern emerged in the prior study, here the soybean oil futures hedging weight is notably lower in the Chicago, New York, and Gulf markets than in the prior study (now ranging from 0.31 to 0.37 compared to 0.43 to 0.56 previously). Also like in the prior study, qualitatively similar patterns or comparisons are apparent in the results of GARCH (1,1) models, albeit with hedging ratios and soybean oil hedging weights slightly higher across the board (Table 9).

Tables 10 and 11 display the number of futures contracts and corresponding gallons of heating oil/diesel and soybean oil to be used in a composite hedges of spot biodiesel price risk for various monthly amounts of biodiesel production, as imputed from error correction and GARCH(1,1) models, respectively. Given the consistencies noted above, the error correction model results for Iowa are again used as an example. The number of heating oil contracts is determined by multiplying the biodiesel quantity hedged (say 100,000 gallons) by the heating oil hedge ratio (0.45) and by the hedging weight for heating oil (1 – 0.90) and then dividing by 42,000 gallons per heating oil futures contract. Similarly, the number of soybean oil futures contracts to use is determined by multiplying the biodiesel quantity hedged (100,000 gallons) by the corresponding hedge ratio (0.58) and hedging weight (0.90) and dividing by 7,815 gallons (or 60,000 pounds per soybean oil futures contract ÷ 7.6776 pounds/gallon of soybean oil).

Reporting the number of both futures contracts to be used in a cross hedge is useful for industry stakeholders that desire to limit exposure to biodiesel spot price risk. However, when using these estimates to interpret the relative importance of each contract for hedging biodiesel price risk, the differences in contract size should be taken into account. The 42,000 gal heating oil futures contract is over five times the size of the 60,000 lb or equivalently 7,947 gal (= 60,000 lb ÷ 7.55 lb /gal) soybean oil futures contract. Across each location, the results suggest that notable weight should be placed on soybean oil futures contracts, and in the production region of Iowa, more so than on the conventionally used heating oil futures contract. For Iowa, the hedging ratio and hedging weight are so small for heating oil that for smaller amounts of biodiesel it may be most practical to hedge with only soybean oil futures contracts—a conclusion that was also drawn by Franken, Irwin, and Garcia (2021).

Conclusions

We apply an encompassing framework to revisit the viability of hedging spot biodiesel price risk for four U.S. markets with a conventionally used heating oil futures contract and a soybean oil futures contract based on the reasoning that supply shifts (i.e., price of soybean oil as an input) drives biodiesel price changes when binding Renewable Fuel Standard (RFS) blending mandates are in place. Events unfolding since a prior study on the topic—including decreased demand for diesel, and hence, biodiesel in an economy constrained by the COVID-19 pandemic and growth renewable diesel driving up soybean oil input prices—could potentially alter price relationships.

We find that, despite apparent changes in price relationships (e.g., Granger causality), soybean oil futures remain an important component of a composite hedge across all market locations studied, and that for the biodiesel production region of Iowa in particular, greater hedging weight should be placed on this futures contract than the conventionally used heating oil futures contract. In fact, for the Iowa market if hedging small quantities of biodiesel, it may be more practical to hedge entirely in the soybean oil futures market. These generalities are consistent with findings of research conducted prior to the aforementioned changes brought about by the COVID-19 pandemic and the policy driven growth of renewable diesel production.

In contrast, although soybean oil remains a sizeable component of the hedge in all markets considered, it is less so than it was in the prior analysis. While hedging ratios for both futures contracts have increased in nearly all markets since then, the hedging ratios for heating oil futures have increased considerably more than those of soybean oil futures, and the hedging weight placed on soybean oil futures is now notably smaller in all markets except Iowa.

Again, these findings remain striking in the context of recent policy decisions. Relaxation of biodiesel blending mandates during the Covid-19 pandemic marked the initial unbinding of those mandates that previously caused the biodiesel prices to be driven by supply shifts, and hence, the price of its primary feedstock—soybean oil. Low carbon fuel standards in California spurred the growth of renewable diesel, another biomass-based diesel fuel, driving up the cost of soybean oil while substituting for diesel and biodiesel demand and thereby curbing their prices. These incidents not only squeezed biodiesel producers' profit margins, but reopened biodiesel prices to demand side risk exposure. The resulting changes in price relationships compromised the previously prescribe hedging strategy, thereby limiting biodiesel producers' ability to effectively manage price risk.

This analysis is limited by small sample size due to the limited time period since the noted policy changes. With time, large samples may be analyzed in future work. Furthermore, in markets outside of the U.S. where other inputs to biodiesel production are more common, there appears to be a lack of tradable hedging vehicles to adequately manage biodiesel price risk (Ziegelback & Kastner, 2011), and this too is a potential avenue for future research.

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Table 1. Summary Statistics.

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Prices on Fridays					
CP^{IA}	134	4.77	1.56	2.51	7.90
FP^{HO}	134	2.16	1.00	0.65	4.78
FP^{ZL}	134	52.03	17.46	25.05	89.17
Prices on Thursdays					
$CP^{Chicago}$	134	4.92	1.65	2.63	8.40
$CP^{New\ York}$	134	4.99	1.74	2.60	8.51
CP^{Gulf}	134	4.94	1.68	2.51	8.36
FP^{HO}	134	2.16	1.01	0.73	5.14
FP^{ZL}	134	51.92	17.44	25.48	90.60

Table 2. Correlations.

	CP^{IA}	FP^{HO}	FP^{ZL}	$CP^{Chicago}$	$CP^{New\ York}$	CP^{Gulf}	FP^{HO}	FP^{ZL}
Prices on Fridays								
CP^{IA}	1.00							
FP^{HO}	0.92	1.00						
FP^{ZL}	0.98	0.89	1.00					
Prices on Thursdays								
$CP^{Chicago}$	0.99	0.95	0.96	1.00				
$CP^{New\ York}$	0.98	0.96	0.96	1.00	1.00			
CP^{Gulf}	0.99	0.95	0.97	1.00	1.00	1.00		
FP^{HO}	0.92	1.00	0.89	0.95	0.96	0.95	1.00	
FP^{ZL}	0.98	0.89	1.00	0.96	0.95	0.97	0.89	1.00

Notes: N=355 for correlations with CP^{Gulf}, 649 for correlations with $CP^{New\ York}$, and 653 for all other correlations.

Table 3. Granger Causality Tests.

Granger Causality Null Hypothesis	Probability > Chi^2 Old	New
CP^{IA} does not Granger-cause FP^{HO}	0.0000	0.0000
FP^{HO} does not Granger-cause CP^{IA}	0.0899	0.0000
CP^{IA} does not Granger-cause FP^{ZL}	0.0000	0.0000
FP^{ZL} does not Granger-cause CP^{IA}	0.0848	0.0000
$CP^{Chicago}$ does not Granger-cause FP^{HO}	0.4828	0.0000
FP^{HO} does not Granger-cause $CP^{Chicago}$	0.3636	0.0000
$CP^{Chicago}$ does not Granger-cause FP^{ZL}	0.0000	0.0000
FP^{ZL} does not Granger-cause $CP^{Chicago}$	0.0367	0.0000
$CP^{New\ York}$ does not Granger-cause FP^{HO}	0.3320	0.0000
FP^{HO} does not Granger-cause $CP^{New\ York}$	0.0000	0.0000
$CP^{New\ York}$ does not Granger-cause FP^{ZL}	0.0000	0.0000
FP^{ZL} does not Granger-cause $CP^{New\ York}$	0.0000	0.0000
CP^{Gulf} does not Granger-cause FP^{HO}	0.1030	0.0000
FP^{HO} does not Granger-cause CP^{Gulf}	0.1594	0.0000
CP^{Gulf} does not Granger-cause FP^{ZL}	0.0000	0.0000
FP^{ZL} does not Granger-cause CP^{Gulf}	0.0770	0.0000

Table 4. Augmented Dickey-Fuller Tests of Stationarity.

Variable	Constant	Trend	Lags with Min AIC	AIC	Test Statistic	Critical Values 1%	5%	10%	Reject Null of Nonstationarity at
Prices on Fridays									
CP^{IA}	yes	yes	0	-.24583088	-2.116	-4.029	-3.446	-3.146	no conventional level
FP^{HO}	yes	yes	1	-.45682352	-3.520	-4.029	-3.446	-3.146	5% & 10%, not 1%
FP^{ZL}	yes	yes	0	4.8995236	-2.107	-4.029	-3.446	-3.146	no conventional level
Prices on Thursdays									
$CP^{Chicago}$	yes	yes	0	-.37225397	-2.550	-4.029	-3.446	-3.146	no conventional level
$CP^{New\ York}$	yes	yes	0	-.37927098	-2.570	-4.029	-3.446	-3.146	no conventional level
CP^{Gulf}	yes	yes	0	-.37990608	-2.549	-4.029	-3.446	-3.146	no conventional level
FP^{HO}	yes	yes	1	-.33915653	-3.561	-4.029	-3.446	-3.146	5% & 10%, not 1%
FP^{ZL}	yes	yes	3	5.0530714	-2.100	-4.030	-3.446	-3.146	no conventional level

Table 5. Augmented Dickey-Fuller Tests of Stationarity of OLS Errors (Cointegration).

Variable	Constant	Trend	Lags with Min AIC	AIC	Test Statistic	Critical Values 1%	5%	10%	Reject null of No Cointegration at
Prices on Fridays									
e_{IA_HO}	no	no	2	0.36625769	-2.036	-2.596	-1.950	-1.612	5% & 10%, not 1%
e_{IA_ZL}	no	no	1	-0.35280794	-2.343	-2.596	-1.950	-1.612	5% & 10%, not 1%
Prices on Thursdays									
$e_{Chicago\_HO}$	no	no	0	-0.38801468	-3.027	-2.596	-1.950	-1.612	all levels
$e_{Chicago\_ZL}$	no	no	1	-0.28531567	-1.345	-2.596	-1.950	-1.612	no conventional level
$E_{NewYork\_HO}$	no	no	0	-0.22440176	-3.296	-2.596	-1.950	-1.612	all levels
$E_{NewYork\_ZL}$	no	no	1	-0.1207618	-1.031	-2.596	-1.950	-1.612	no conventional level
E_{Gulf_HO}	no	no	0	-0.33851853	-3.038	-2.596	-1.950	-1.612	all levels
E_{Gulf_ZL}	no	no	1	-0.27455482	-1.480	-2.596	-1.950	-1.612	no conventional level

Table 6. Johansen's Test of Cointegration.

Series	Rank r	Trace Test: Test statistic	Trace Test: Critical Value 1%	Trace Test: Critical Value 5%	Max Eigenvalue test: Test statistic	Max Eigenvalue test: Critical Value 1%	Max Eigenvalue test: Critical Value 5%
IA, HO	0	11.6422**	20.04**	15.41*	11.4934**	18.63**	14.07*
	1	0.1488	6.65	3.76	0.1488	6.65	3.76
IA, ZL	0	36.6501	20.04	15.41	35.1796	18.63	14.07
	1	1.4704**	6.65**	3.76*	1.4704**	6.65**	3.76*
Chicago, HO	0	9.3441**	20.04**	15.41*	9.2886**	18.63**	14.07*
	1	0.0555	6.65	3.76	0.0555	6.65	3.76
Chicago, ZL	0	20.9806	20.04	15.41	18.7764	18.63	14.07
	1	2.2042**	6.65**	3.76*	2.2042**	6.65**	3.76*
New York, HO	0	11.6665**	20.04**	15.41*	11.6457**	18.63**	14.07*
	1	0.0207	6.65	3.76	0.0207	6.65	3.76
New York, ZL	0	18.5855**	20.04**	15.41	16.3705**	18.63**	14.07
	1	2.2150*	6.65	3.76*	2.2150*	6.65	3.76*
Gulf, HO	0	9.2216*	20.04*	15.41*	9.1126**	18.63**	14.07*
	1	0.1090	6.65	3.76	0.1090	6.65	3.76
Gulf, ZL	0	21.8908	20.04	15.41	19.8665	18.63	14.07
	1	2.0242**	6.65**	3.76*	2.0242**	6.65**	3.76*

Uses lags from next table.

Table 7. SIC Minimizing Model Structure for Results Reported in Table 8.

$P_t - P_{t-4}$	Min SIC	Structure	Significance of Lagged Residual
IA, HO	-2.52	1 lag of price changes, lagged residual	1% level
IA, ZL	-3.19	1 lag of price changes, lagged residual	1% level
Chi, HO	-3.62	2 lags of price changes, no lagged residual	N.A.
Chi, ZL	-3.22	1 lag of price changes, lagged residual	5% level
NY, HO	-3.68	2 lags of price changes, lagged residual	1% level
NY, ZL	-3.14	1 lag of price changes, no lagged residual	N.A.
Gulf, HO	-3.61	2 lags of price changes, lagged residual	5% level
Gulf, ZL	-3.25	1 lag of price changes, lagged residual	5% level

Note: For each price pair, eight models including various combinations of an error correction term and up to three lags of each price are evaluated, with the chosen structure based on minimization of SIC.

Table 8. Hedging Results using an Error Correction Model.

	Iowa		Chicago		New York		Gulf of Mexico	
Hedging Regressions	Heating Oil	Soybean Oil	Heating Oil	Soybean Oil	Heating Oil	Soybean Oil	Heating Oil	Soybean Oil
Estimated Hedge Ratio (β)	0.45	0.58	0.83	0.57	0.82	0.53	0.84	0.59
(Standard Error)	(0.10)	(0.07)	(0.08)	(0.11)	(0.07)	(0.11)	(0.05)	(0.10)
N	129	129	128	129	128	129	128	129
F	46.50	97.55	89.23	79.39	79.98	89.79	127.57	82.32
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R^2	0.6790	0.8361	0.8627	0.7892	0.8660	0.7556	0.8635	0.7897
Standard Deviation (e_t)	0.26	0.19	0.15	0.18	0.14	0.19	0.14	0.18
Correlations ($\rho e_0 e_1$)	0.63		0.20		0.23		0.17	
Encompassing Regression								
Estimated Hedging Weight (λ)		0.90		0.37		0.31		0.37
(Standard Error)		(0.10)		(0.08)		(0.08)		(0.08)
N		129		128		128		128
R^2		0.4951		0.2725		0.2127		0.2938

Note: Based on minimum SIC, optimal model for both Iowa regressions includes 1 lag of price changes and a lagged residual; for Chicago-Heating Oil includes 2 lags of price changes and no lagged residual and for Chicago-Soybean Oil includes 1 lag of price changes and a lagged residual; New York-Heating Oil and Gulf-Heating Oil include 2 lags of price changes and a lagged residual; New York-Soybean Oil includes 1 lag of price changes and no lagged residual; and Gulf-Soybean Oil includes 1 lag of price changes and a lagged residual. Robust standard errors are reported in cases where evidence of heteroskedasticity is found.

Table 9. Hedging Results using a GARCH(1,1) Model.

	Iowa		Chicago		New York		Gulf of Mexico	
Hedging Regressions	Heating Oil	Soybean Oil	Heating Oil	Soybean Oil	Heating Oil	Soybean Oil	Heating Oil	Soybean Oil
Estimated Hedge Ratio (β)	0.33	0.74	0.95	0.71	0.90	0.61	0.70	0.73
(Standard Error)	(0.04)	(0.07)	(0.04)	(0.05)	(0.03)	(0.06)	(0.09)	(0.06)
N	130	130	130	130	130	130	130	130
Wald chi2(9)	1382.28	383.75	2793.68	906.27	1567.15	190.26	71.17	168.08
Prob > chi2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Log pseudolikelihood	-16.56	13.59	43.99	37.89	38.10	26.27	8.59	25.22
Standard Deviation (e_t)	0.38	0.27	0.25	0.25	0.26	0.26	0.27	0.25
Correlations ($\rho e_0 e_1$)	0.65		0.35		0.43		0.48	
Encompassing Regression								
Estimated Hedging Weight (λ)		0.92		0.50		0.51		0.58
(Standard Error)		(0.10)		(0.08)		(0.09)		(0.09)
N		130		130		130		130
R^2		0.4867		0.3282		0.2886		0.3215

Table 10. Number of Futures Contracts to Hedge Biodiesel Production Based on an Error Correction Model.

		Monthly Biodiesel Production (Gallons)						
Location	Futures Contract	100,000	200,000	400,000	600,000	800,000	1,000,000	10,000,000
Number of Futures Contracts								
Iowa	Heating Oil	0.1	0.2	0.4	0.6	0.9	1.1	10.7
	Soybean Oil	6.6	13.1	26.3	39.4	52.5	65.7	656.9
Chicago	Heating Oil	1.2	2.5	5.0	7.5	10.0	12.5	124.5
	Soybean Oil	2.7	5.3	10.6	15.9	21.2	26.5	265.4
New York	Heating Oil	1.3	2.7	5.4	8.1	10.8	13.5	134.7
	Soybean Oil	2.1	4.1	8.3	12.4	16.5	20.7	206.7
Gulf	Heating Oil	1.3	2.5	5.0	7.6	10.1	12.6	126.0
	Soybean Oil	2.7	5.5	11.0	16.5	22.0	27.5	274.7
Number of Gallons								
Iowa	Heating Oil	4,500	9,000	18,000	27,000	36,000	45,000	450,000
	Soybean Oil	52,200	104,400	208,800	313,200	417,600	522,000	5,220,000
Chicago	Heating Oil	52,290	104,580	209,160	313,740	418,320	522,900	5,229,000
	Soybean Oil	21,090	42,180	84,360	126,540	168,720	210,900	2,109,000
New York	Heating Oil	56,580	113,160	226,320	339,480	452,640	565,800	5,658,000
	Soybean Oil	16,430	32,860	65,720	98,580	131,440	164,300	1,643,000
Gulf	Heating Oil	52,920	105,840	211,680	317,520	423,360	529,200	5,292,000
	Soybean Oil	21,830	43,660	87,320	130,980	174,640	218,300	2,183,000

Table 11. Number of Futures Contracts to Hedge Biodiesel Production Based on a GARCH(1,1) Model.

		Monthly Biodiesel Production (Gallons)						
Location	Futures Contract	100,000	200,000	400,000	600,000	800,000	1,000,000	10,000,000
Number of Futures Contracts								
Iowa	Heating Oil	0.1	0.1	0.3	0.4	0.5	0.6	6.3
	Soybean Oil	8.6	17.1	34.3	51.4	68.5	85.7	856.7
Chicago	Heating Oil	1.1	2.3	4.5	6.8	9.0	11.3	113.1
	Soybean Oil	4.5	8.9	17.9	26.8	35.7	44.7	446.7
New York	Heating Oil	1.1	2.1	4.2	6.3	8.4	10.5	105.0
	Soybean Oil	3.9	7.8	15.7	23.5	31.3	39.1	391.5
Gulf	Heating Oil	0.7	1.4	2.8	4.2	5.6	7.0	70.0
	Soybean Oil	5.3	10.7	21.3	32.0	42.6	53.3	532.8
Number of Gallons								
Iowa	Heating Oil	2,640	5,280	10,560	15,840	21,120	26,400	264,000
	Soybean Oil	68,080	136,160	272,320	408,480	544,640	680,800	6,808,000
Chicago	Heating Oil	47,500	95,000	190,000	285,000	380,000	475,000	4,750,000
	Soybean Oil	35,500	71,000	142,000	213,000	284,000	355,000	3,550,000
New York	Heating Oil	44,100	88,200	176,400	264,600	352,800	441,000	4,410,000
	Soybean Oil	31,110	62,220	124,440	186,660	248,880	311,100	3,111,000
Gulf	Heating Oil	29,400	58,800	117,600	176,400	235,200	294,000	2,940,000
	Soybean Oil	42,340	84,680	169,360	254,040	338,720	423,400	4,234,000

FOR APPENDIX OR AVAILABLE UPON REQUEST

****************************8 week horizon*************************************

Table 7.8. SIC Minimizing Model Structure for Results of 8-week Horizon.

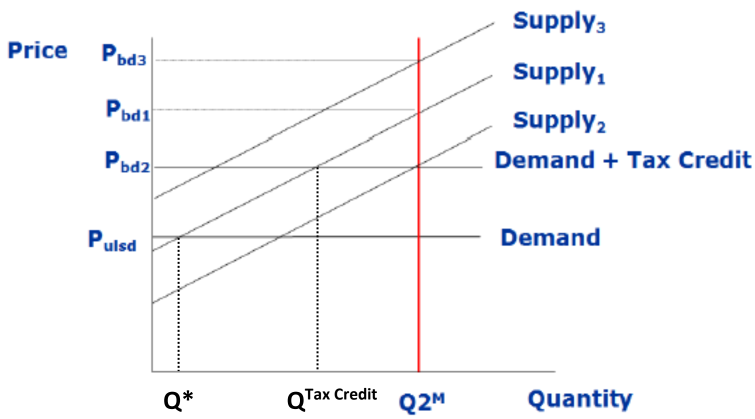
P_t - P_{t-4}	Min SIC	Structure	Significance of Lagged Residual
IA, HO	-2.38	1 lag of price changes, lagged residual	1% level
IA, ZL	-3.14	2 lags of price changes, lagged residual	1% level
Chi, HO	-3.50	2 lags of price changes, lagged residual	5% level
Chi, ZL	-3.30	1 lag of price changes, no lagged residual	5% level
NY, HO	-3.47	2 lags of price changes, lagged residual	5% level
NY, ZL	-3.19	1 lag of price changes, no lagged residual	N.A.
Gulf, HO	-3.47	2 lags of price changes, lagged residual	5% level
Gulf, ZL	-3.30	1 lag of price changes, lagged residual	10% level

Note: For each price pair, eight models including various combinations of an error correction term and up to three lags of each price are evaluated, with the chosen structure based on minimization of SIC.

Table 8.8 Hedging Results using an Error Correction Model – 8-week Horizon.

	Iowa		Chicago		New York		Gulf of Mexico	
Hedging Regressions	Heating Oil	Soybean Oil	Heating Oil	Soybean Oil	Heating Oil	Soybean Oil	Heating Oil	Soybean Oil
Estimated Hedge Ratio (β)	0.42	0.64	0.78	0.50	0.79	0.48	0.78	0.54
(Standard Error)	(0.14)	(0.14)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
N	125	124	124	125	124	125	124	125
F	177.95	256.41	251.19	237.94	227.93	204.51	240.63	184.17
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R^2	0.8447	0.9332	0.9270	0.8998	0.9220	0.8835	0.9199	0.8969
Standard Deviation (e_i)	0.28	0.18	0.15	0.18	0.15	0.19	0.15	0.18
Correlations ($\rho e_0 e_1$)	0.55		0.31		0.36		0.32	
Encompassing Regression								
Estimated Hedging Weight (λ)		0.90		0.39		0.35		0.41
(Standard Error)		(0.08)		(0.07)		(0.07)		(0.07)
N		124		124		124		124
R^2		0.5746		0.2461		0.1923		0.2561

Note: Based on minimum SIC, optimal regression models for Iowa-Heating Oil includes 1 lag of price changes and a lagged residual and for Iowa-Soybean Oil includes 2 lags of price changes and a lagged residual; for Chicago-Heating Oil includes 2 lags of price changes and a lagged residual and for Chicago-Soybean Oil includes 1 lag of price changes and no lagged residual; New York-Heating Oil and Gulf-Heating Oil include 2 lags of price changes and a lagged residual; New York-Soybean Oil includes 1 lag of price changes and no lagged residual; and Gulf-Soybean Oil includes 1 lag of price changes and a lagged residual. Robust standard errors are reported in cases where evidence of heteroskedasticity is found.



Source: Adapted from Irwin (2015).

Figure 1. Biodiesel Market with a Volume Mandate, Blender Tax Credit, and Supply Shifts

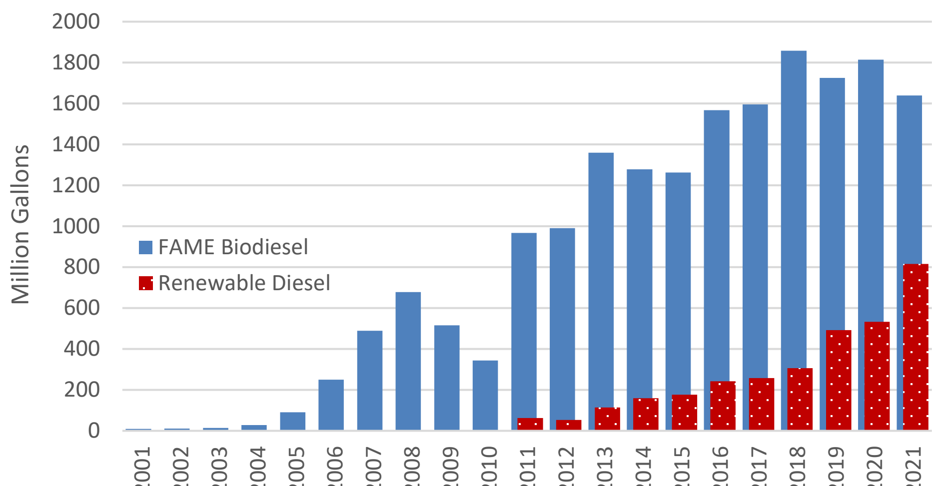


Figure 2. Biodiesel and Renewable Diesel Production

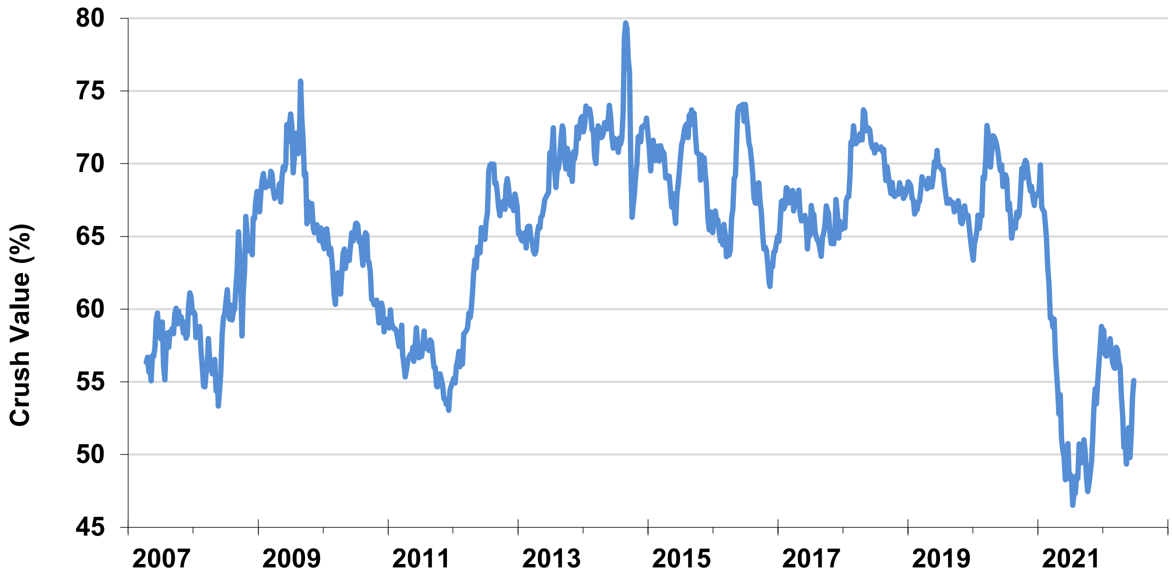


Figure 3. Weekly Soybean Meal Share of Crush Value at Iowa Plants, 4/13/2007-6/24/2022

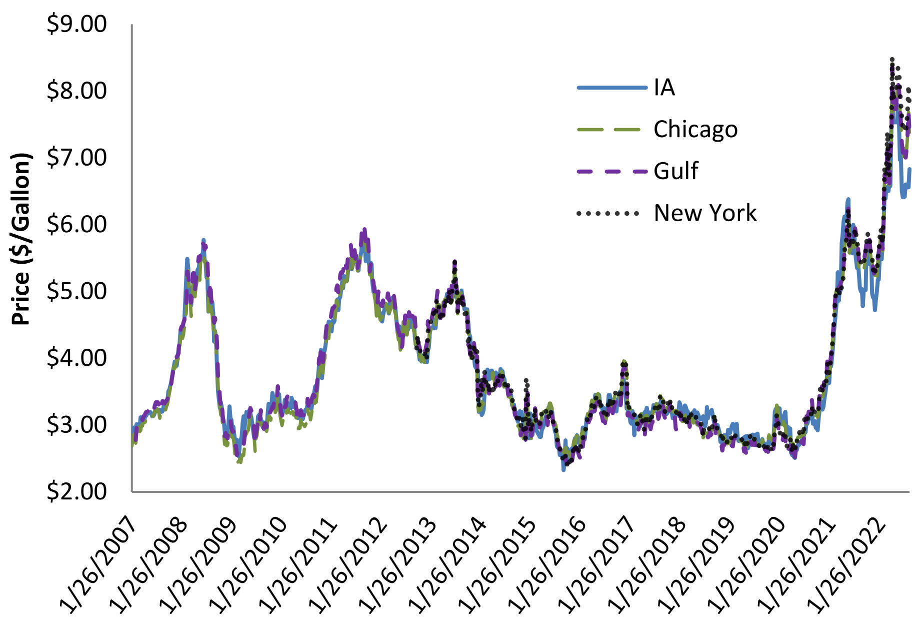


Figure 4. Historic Biodiesel Cash Prices, January 26, 2007 through September 2, 2022