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FUTURES PRICES LINKAGES IN THE US SOYBEAN COMPLEX

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Abstract

This work investigates the linkages among the futures prices of soybeans, soybean meal, and soybean oil in the US. This has been pursued using a flexible methodology that allows modelling price relationships at different parts of their joint distribution. According to the empirical results, the markets are strongly connected in the vertical direction regardless of the sign and the size of shocks. The meal and oil prices maintain a negative relationship at the median and the upper quantiles**,** but they are not connected under large negative shocks. The soybean market is a net transmitter of price risk to the other two markets, while price shocks around the median tend to be transmitted with higher intensity relative to those at the extremes.

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1. Introduction

Soybean is the second largest row crop in the US. It is processed ("crushed") in two joint products: soybean meal and soybean oil. Soybean meal is predominantly used as a protein source in livestock feed ratios. Soybean oil has been traditionally used for human consumption (cooking oil, salad dressings, etc.). In recent years, however, an increasing part of it has been utilised as an input in biodiesel production[1].

The futures markets for soybeans and its products in the US are among the oldest and the most liquid ones. The linkages among the futures prices of soybean, meal, and oil are important for farmers, processors, soybean meal and oil users, futures markets participants, and policymakers. Farmers typically enter the futures markets to hedge their exposure to soybeans' price risk. Processors are primarily interested in establishing a floor for their "crush spread" (the difference between the combined value of meal and oil and the value of soybeans used to produce them). To this end, they typically long (sell) the crush spread by buying soybean futures contracts and selling meal and oil contracts. Speculators may long or short (sell) the crush spread, depending on whether they expect

[1] Brazil (with 36 %) is the biggest producer of soybeans, followed by the US (29%), Argentina (16%), and China (5%); China (with 29%) is the biggest producer of soybean meal, followed by the US (19%), Brazil (17%), and Argentina (11%); China (with 27%) is the biggest producer of soybean oil followed by the US (20%), Brazil (17%), and Argentina (11%). The top exporter of soybeans is Brazil and the top importer is China; the top exporter of soybean meal is Argentina and the top importer is the EU-28; the top exporter of soybean oil is again Argentina and the top importers are India and China (https://www.fao.org/statistics/en/)"

it to get wider or narrower in the future[2]. Policymakers are mainly concerned with the well-functioning of markets and the viability of the relevant industries.

The US soybean complex potentially presents a special interest for research economists since it involves price relationships in two directions: the vertical (between soybeans and its products) and the horizontal (between meal and oil). The type (positive or negative), the intensity (strong or weak), and the mode (symmetric or asymmetric) of these linkages contain useful information for assessing the well-functioning of the network of the three interrelated markets and for designing appropriate risk management strategies (e.g., Mayer and von Cramon Taubadel, 2004; Reboredo, 2012, Hautsch *et al.*, 2015). As noted by Collins (2000), profits of firms with multiple commodity endowments (such as the soybean processing ones) are to some degree "self-hedged" provided that input and output prices are positively correlated and hedging one commodity in isolation may actually increase the overall level of risk. It is surprising, therefore, that the number of empirical works on the topic is quite small.

Rausser and Carter (1983), assessed the efficiency of futures markets in the US soybean complex using a structurally based Autorergessive Integrated Moving Average (ARIMA) model. They obtained some evidence of inefficiency for the soybean and soybean meal markets but not for the soybean oil market. Beutler and Brorsen (1985) investigated the lag-lead relationships among daily spot (cash) prices of soybeans, meal, and oil using a 3-variate VAR model. They found that the input price led to the products' prices and that past oil prices had a negative effect on meal prices. Collins (2000) compared alternative strategies for minimising the day-to-day variability of the crush spread. According to his results, multivariate or univariate risk-minimizing models offered no risk-management advantages over a simple equal and opposite hedge[3]. Babula *et al.* (2004), using cash prices, multivariate VAR models, Directed Acyclical Graphs, and Forecast Error Variance Decompositions (FEVD), reported bi-directional causality between soybeans and meal and uni-directional causality from soybeans to oil. Adrangi *et al.* (2006), using futures prices and bi-variate VECM models ((soybeans, meal) and (soybeans, oil)) found that each pair of prices was cointegrated and that the prices of meal and oil were weakly exogenous. Finally, Simanjuntak *et al.* (2020), using Rotterdam soybean prices, Hamburg meal prices, and Dutch oil prices, and a 3-variate VECM model found one cointegrating vector and that the price of soybean bears the burden of convergence to the long-run equilibrium.

A common characteristic of the above-mentioned empirical works is that they investigated price relationships in the soybean complex "on average" (i.e., around the mean of their joint distribution). However, there is no *a priori* reason to assume that the pattern of linkages is the same under different signs and sizes of shocks. Quite the contrary. There is plenty of empirical evidence that the type, intensity, and mode of a relationship among stochastic processes may be quantile-dependent (e.g., Barunik and Kley, 2019; Ando *et al.*, 2022).

The present work revisits futures prices linkages in the US soybean complex. In doing so, it departs from the existing literature in two important ways. First, it relies on a flexible methodology, proposed by Hautsch *et al.* (2015), that allows modelling relations at different parts of the 3-variate (joint) price distribution and in two directions (vertical and horizontal)[4]. Second, it employs a barrage of statistical tests to identify and quantify asymmetric linkages with respect to the sign, size, and origin (a particular market in the complex) of price shocks. Quantile-dependent and asymmetric price relationships are important for risk management in the soybean complex because hedging strategies that may be suitable for one part of the joint price distribution (i.e. for a given state of markets) may be unsuitable for another part of it. For example, if prices do not move in the same direction at certain quantiles,

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[2] https://www.cmegroup.com/education/files/soybean-crush-reference-guide.pdf.

[3] That type of hedge involves taking equal and opposite positions in the spot (cash) and futures markets (so that gain (loss) in one market is offset by loss (gain) in the other market and the hedger's risk exposure is reduced or eliminated).

[4] Among the recent applications of the approach by Hautsch *et al.* (2015) are the works of Ngugen *et al.* (2020) on cryptocurrencies, Fousekis and Grigoridis (2022) on international coffee markets, and Fousekis (2022) on the EU olive oil markets.

profit is no longer "self-hedged"; strategies, therefore, that are based on the information about price co-movement "on average" may actually increase risk. Earlier empirical studies on the linkages between soybeans, soybean meal, and soybean oil prices have failed to consider this possibility. Section 2 presents the analytical framework, and Section 3 the data, the empirical models and the empirical results. Section 4 offers conclusions and suggestions for future research.

2. Analytical Framework

Let r_t^i be a stationary stochastic process (here, the price-log return of given Commodity *i*) at *t*= 1, 2, …, *T*. The *lower-tail value-at-risk* ($VaR_{q,t}^{i,L}$) is the *q*th quantile of the unconditional distribution of r_t^i (with $q \in (0, 0.5)$); it gives the maximum value r_t^i will attain with confidence level 1-*q*. Let now r_t^j be another stationary stochastic process. The *lower-tail conditional value-at-risk* ($CoVaR_{q,t}^{i/j,L}$) is the *q*th quantile of the conditional distribution of r_t^i; it gives the maximum value r_t^i will attain with confidence level 1-*q*, provided that $r_t^j \leq VaR_{q,t}^{j,L}$. (e.g., Adrian & Brunnermeier, 2011; Borri, 2019). The *upper-tail conditional value-at-risk* ($CoVaR_{q,t}^{i/j,U}$) is defined analogously; it is the (1-*q*)th of the conditional distribution of r_t^i; it gives the minimum value r_t^i will attain with confidence level 1-*q*, provided that $r_t^j \geq VaR_{1-q,t}^{j,U}$.

The notions of conditional lower- and upper-tail value-at-risk can be easily extended to multiple conditioning stochastic processes. For a *n*x1 vector of stationary stochastic processes the *q*th quantile of the conditional distribution of r_t^i is

$$q = prob\left(r_t^i \leq \frac{VaR_{q,t}^{i,L}}{r_t^1} \leq VaR_{q,t}^{1,L}, r_t^2 \leq VaR_{q,t}^{2,L}, \ldots, r_t^n \leq VaR_{q,t}^{n,L} \right) \tag{1}$$

while the (1-*q*)th quantile of it is

$$q = prob\left(r_t^i \geq \frac{VaR_{1-q,t}^{i,U}}{r_t^1} \geq VaR_{1-q,t}^{1,U}, r_t^2 \geq VaR_{1-q,t}^{2,U}, \ldots, r_t^n \geq VaR_{1-q,t}^{n,U} \right) \tag{2}$$

The standard quantile regression (Koenker and Bassett, 1978) offers an efficient way to implement empirically a *CoVaR* model. For the lower-tail *CoVaR*, Hautsch *et al.* (2015) and Ngueyen *et al.* (2020) proposed the estimation of

$$VaR_{q,t}^{i,L} = a_q^{i,L} + \sum_{j=1, j\neq i}^{n-1} \beta_q^{i/j,L} E_{q,t}^{j,L} + \sum_{k=1}^{K} \gamma_q^{i/k} Z_{q,t}^k + u_{q,t}^{i,L} \tag{3}$$

where $E_{q,t}^{j,L}$ is the *loss exceedance* for r_t^j (a variable defined as $E_{q,t}^{j,L} = r_t^j$ for $r_t^j \le VaR_{q,t}^{j,L}$ and $E_{q,t}^{j,L} = 0$ otherwise), Z_k are other relevant variables, and $u_{t,q}^{iL}$ is the error term. The coefficient $b_q^{i/j,L}$ in (3) represents the sensitivity of r_t^i to negative shocks in r_t^j. $b_q^{i/j,L} > 0$ implies that values of $r_t^{j,L}$ below $VaR_{q,t}^{j,L}$ increase the probability of observing values of r_t^i below $VaR_{q,t}^{i,L}$; $b_q^{i/j,L} = 0$ suggests that there is no price-risk transmission from commodity *j* to *i*, at the *q*th quantile; finally, $b_q^{i/j,L} < 0$ implies that values of $r_t^{j,L}$ below $VaR_{q,t}^{j,L}$ decrease the probability of observing values of r_t^i below $VaR_{q,t}^{i,L}$ (in the latter case, therefore, extreme negative price shocks to commodity *j* may result into weak negative or even positive returns for *i*). For the upper-tail *CoVaR*, the interpretation of the model coefficients is analogous (i.e., a zero coefficient suggests no sensitivity of *i* to positive shocks to *j* whereas a positive (negative) sign implies that a positive shock to *j* increases (decreases) the probability of observing values of *i* above $VaR_{1-q,t}^{i,U}$).

The regression coefficients at quantile thresholds *q* and 1-*q* allow one to test a number of alternative hypotheses about the structure of price linkages. The sign and the statistical significance of $b_q^{i/j,L} - b_{1-q}^{i/j,U}$ provides information on the relative intensity of the transmission of price shocks at symmetric lower- and upper-quantiles (e.g., a positive and statistically significant difference will imply that shocks to *j* at the *q*th quantile are transmitted to *i* with higher intensity relative those at the (1-*q*)th quantile, while a zero difference will point to symmetric transmission with respect to the sign and the size of price shocks). The sign and the statistical significance of $b_q^{i/j,L} - b_q^{j/i,L}$ (or equivalently that of $b_{1-q}^{i/j,U} - b_{1-q}^{j/i,U}$) provides information on asymmetry with respect to the origin of shocks; that means, information on which of the two commodities is likely to be net-transmitter of price risk (e.g., Barunik *et al.*, 2016; Nguyen *et al.*, 2020; Fousekis & Grigoriadis, 2022).

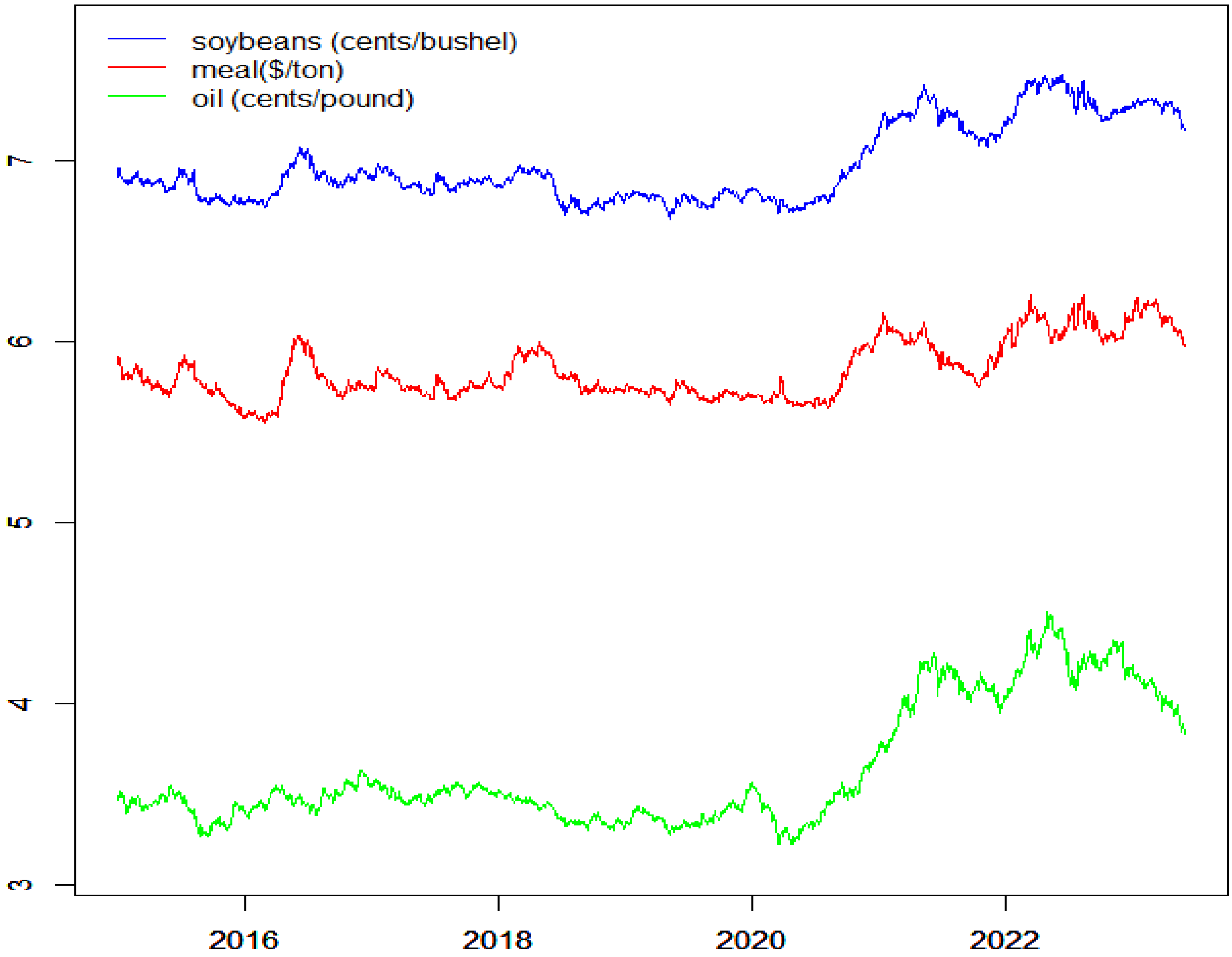
3. Data, Empirical Models, and Results

31. Data

The data for the empirical analysis are closing front-month daily prices of soybeans (in cents/bushel), soybean meal (in $/short ton), and soybean oil (in cents/pound). They were obtained from Yahoo Finance, and they refer to the period 1/1/2015 to 5/31/2023[5]. Figure 1 presents the evolution of (logarithmic) futures prices over the sample period.

[5] Price information for earlier periods is available. The sample size here has been restricted to recent periods to capture the effect of the dramatic increase in the use of soybean as an input in biodiesel production. According to the ERS-USDA, the part of domestically consumed oil directed to biodiesel production was rather small prior to 2010 but it rose from 26.4 % in 2015 to 42.9% in 2022 (https://www.ers.usda.gov/data-products/oil-crops-yearbook/). The number of observations (2115) is more than sufficient for a robust statistical analysis while empirical results based on recent information are far more relevant for policy analysis and risk-management purposes. Each Chicago Board of Trade (CBOT) soybean contract consists of 5000 bushels (or 136.1 metric tons); the soybean meal and soybean oil contracts consist of 10 metric tons each. Over the sample period, the average values of contracts traded (i.e., the volume) were 76540, 31310 and 33813 per day for soybeans, meal, and oil respectively. Traded volume in all cases has exhibited a positive (although rather weak) trend. The average values of open interest, during 2019-23, were 750000, 430000, and 400000 per day for soybeans, soybean meal, and soybean oil, respectively.

Figure 1: The evolution of (logarithmic) futures prices

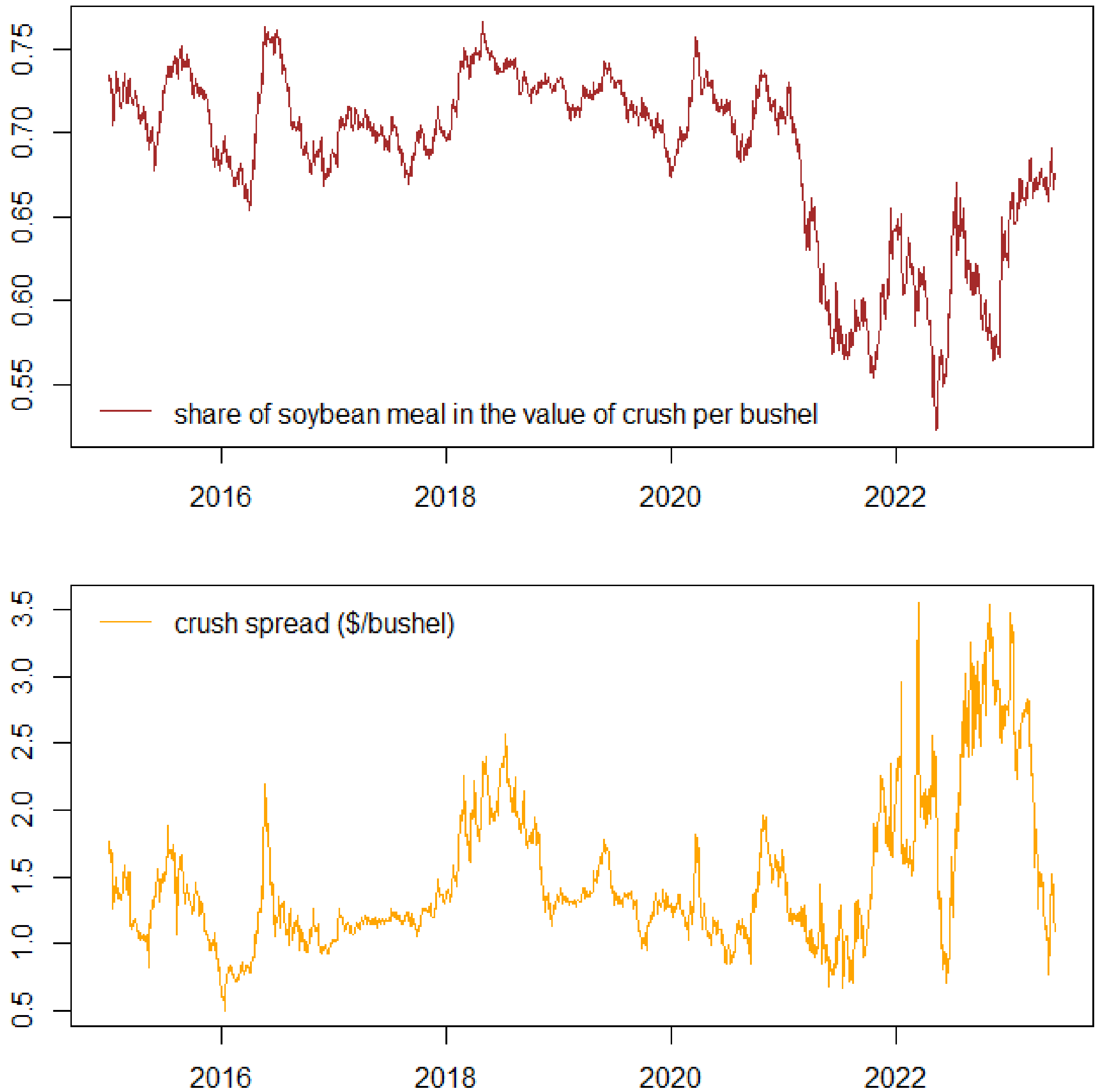


The three series followed similar trends until the first months of 2020. Since then, the price of oil has risen by about 57% of soybeans by 42%, and soybean meal by about 35 %.

Processing soybeans typically results in 80% meal and 18% oil (the exact proportions depend on soybean characteristics and the processing technology utilised). Historically, soybean meal had been the dominant source of demand for soybeans. The emergence of the biodiesel industry combined with the decline in soybean oil for domestic food use and the relatively stable demand for animal feed has induced processors to switch from "crushing for meal" to "crushing for oil" (Wisner, 2015; Gerdts, 2022). These developments have led to a sharp decline in the share of meal in the value of soybean crush, especially in the last three years (Figure 2, top). The crush spread showed considerable volatility about its mean value (1.5$ per bushel), especially since the late-2021 (Figure 2, bottom). All prices (in natural logs) are non-stationary at any reasonable level of significance; their, log-returns, however, are (weakly) stationary[6]. Therefore, the subsequent analysis here relies on log-returns.

[6] The properties of the log-levels and the log-returns have been verified through the KPSS tests. The results are available upon request.

Figure 2: The evolution of the share of meal in the value of crush (top) and the crush spread (bottom) per bushel of soybeans



Note: Author's calculations based on the relevant CME Group Guide.

3.2 Empirical Models and Results

Table 1 reports unconditional and conditional Pearson's contemporaneous correlation coefficients for the three pairs of log-returns; the unconditional range from 0.13 for meal and oil to 0.75 for soybeans and meal. Partial (conditional) correlation coefficients quantify the linear association between two stochastic processes when conditioned for one or more confounding variables, avoiding, thus, spurious correlation. The conditional correlations (calculated as suggested by Kim (2015) for soybeans and meal and soybeans and oil are higher than the corresponding unconditional ones while that for meal and oil is negative. Moreover, the differences are statistically significant. It is obvious that bi-variate modelling (as in Adrangi *et al*. (2006)) is not suitable for investigating the price linkages in the US soybean complex. The negative sign for the pair meal and oil makes perfect sense if one takes into account that meal and oil are produced jointly in (almost) fixed proportions. As the demand for oil rises (in recent years, this is precisely the case with the rapid growth in the biodiesel industry), more soybeans are crushed, increasing the supply of both meal and oil. When the demand for meal is stagnant or rises at a slower pace relative to that for oil, the "crushing for oil" will exercise downward pressure on meal prices. Gerdts (2022) argued that the relationship between oil and meal prices may be negative without, however, offering any empirical evidence of it. Adrangi *et al*. (2006) did not investigate the association between meal and oil prices; Simanjuntak *et al*. (2020) reported a single cointegrating vector in which the price of soybeans depended positively on the prices of the two joint products while the FEVD (as in Babula *et al*., 2004) does not provide any information on whether a relationship is positive or negative. The study by Beutler and Brorsen (1985) is the only one that found a negative (although a lag-lead one) impact of soybean oil prices on meal prices.

Table 1: Unconditional and Conditional Pearson Contemporaneous Correlation Coefficients Between Log-Returns

Index pair	Unconditional (1)	Conditional (2)	Difference =(2)-(1)
(Soybeans, Soybean Meal)	0.745	0.812	0.068
(Soybeans, Soybean Oil)	0.555	0.687	0.132
(Soybean Meal, Soybean Oil)	0.135	-0.501	-0.637

Note: All estimates in Table 1 are statistically significant at the 1 per cent level or less (a result obtained using bootstrap with 1000 replications).

The number of possible quantile thresholds for estimating model (3) (and the corresponding for the upper-tail CoVAR) is infinite. Following earlier studies on the topic (e.g., Nguyen *et al*., 2020; Fousekis & Grigoriadis, 2022), the present work focuses on a small number of them and, in particular, on the 5% lower, the median, and the 5% upper. The *CoVaR* model for each price return and each quantile threshold includes as control variables the corresponding exceedance levels of the other two price returns and (to account for possible autocorrelation) lags of the dependent variable[7].

The empirical analysis involves a number of single and joint coefficient tests. These have been conducted using a Wald-type statistic

$$W = (R\hat{C})'(R\hat{V}_C R')^{-1}(R\hat{C}) \qquad (4)$$

where R is the restrictions' matrix, C is the parameters' vector, and $\hat{V}_C$ is the bootstrap estimate of their variance-covariance matrix (Patton, 2013). Under a null, Ω follows the C^2 distribution with degrees of freedom equal to the number of restrictions.

Table 2 shows the sensitivity coefficients at the three quantile thresholds. At the lower 5% tail, the impact of changes in soybean prices on both meal and oil prices is positive and strongly statistically significant, and the same is true for the impact of changes in the prices of meal and oil on soybean prices. Therefore, there is plenty of evidence that the price pairs (soybeans, meal) and (soybeans, oil) tend to crush together. The two sensitivity coefficients for the pair (meal, oil), although positive, are not significant at any reasonable level. A non-zero sensitivity coefficient, points to the presence of information flow between markets and is an indication of market integration (Mayer and von Cramon Taubadel, 2004; Reboredo, 2011). From the results in Table 2, one may conclude that, at the 5 % lower tail, there is information flow both upstream and downstream and that the market pairs (soybean,

[7] For each quantile regression, the optimal lag length has been determined using the conservative Schwartz Criterion. The empirical models have been estimated using the routine *dynrq* (Package "quantreg" in R; Koenker, 2023).

meal) and (soybean, oil) are integrated. At the median and at the 5% upper tail the sensitivity coefficients for the pairs (soybeans, meal) and (soybeans, oil) are also positive and strongly statistically significant; the sensitivity coefficients, however, for the pair (meal, oil) are all negative and statistically significant at the 2.5% level (or less). The absence of a link between meal and oil at the lower tail and the negative links at the median and the upper tail may complicate, ceteris paribus, crush hedging behind which lies the idea that prices of the two joint products will move up and down together and it may create opportunities for speculators to profit from “beating” the market.

Table 2: Sensitivity coefficients

Pairs	5% Lower-tail	Median	5% Upper-tail
(Soybeans® Meal)	1.074 (<0.01)	1.455 (<0.01)	0.953 (<0.01)
(Soybeans® Oil)	1.449 (<0.01)	1.638 (<0.01)	1.027 (<0.01)
(Meal® Oil)	0.026 (0.928)	-0.881 (<0.01)	-0.360 (<0.01)
(Meal® Soybeans)	0.680 (<0.01)	0.815 (<0.01)	0.658 (<0.01)
(Oil® Soybeans)	0.524 (<0.01)	0.516 (<0.01)	0.355 (<0.01)
(Oil® Meal)	0.073 (0.760)	-0.473 (<0.01)	-0.146 (-0.025)

Note: p-values in parentheses; obtained using bootstrap with 1000 replications.

Table 3 shows tests on the equality of the sensitivity coefficients at the three selected quantile thresholds. In all cases, the null hypothesis of symmetry has been strongly rejected suggesting that sign and the size of price shocks do matter for the pattern of information transmission from one market to the other. To shed more light on this important issue, Table 4 presents tests on the equality of sensitivity coefficients at the upper and the lower tails only. The null has been rejected only for oil and soybeans (when the price shock originates from oil). The positive sign of the test statistic in this case suggests that lower- tail shocks are transmitted with higher intensity relative to upper- tail ones. Taken together, Tables 3 and 4, imply that transmission asymmetries with respect to the sign and the size of shocks are more likely to occur between the median and the tails than between the tails of the joint distribution.

Table 3: Three-Coefficient Symmetry Tests with Respect to the Sign and the Size of Price Shocks

(Ho: The sensitivity coefficients are equal at the 5% lower, the median, and the 5% upper quantiles)

Pairs	Empirical values
(Soybeans® Meal)	-0.381 and 0.503 (<0.01)
(Soybeans® Oil)	-0.189 and 0.610 (<0.01)
(Meal® Oil)	0.907 and -0.21 (<0.01)
(Meal® Soybeans)	-0.135 and 0.157 (0.032)
(Oil® Soybeans)	0.009 and 0.161 (0.304)
(Oil® Meal)	0.547 and -0.327 (<0.01)

Note: (a) The empirical values are coefficient at the 5% lower-tail minus coefficient at the median and coefficient at the median minus coefficient at the 5% upper-tail. (b) p-values in parentheses; obtained using bootstrap with 1000 replications.

Table 4: Two-Coefficient Symmetry Tests with Respect to the Sign and the Size of Price Shocks

(Ho: The sensitivity coefficients are equal at the 5% lower, the median, and the 5% upper quantiles)

Pairs	Empirical value
(Soybeans® Meal)	0.121 (0.459)
(Soybeans® Oil)	0.421 (0.127)
(Meal® Oil)	0.386 (0.209)
(Meal® Soybeans)	0.021 (0.845)
(Oil® Soybeans)	0.169 (0.016)
(Oil® Meal)	0.219 (0.372)

Note: (a) The empirical values are coefficient at the 5% lower-tail minus coefficient at the 5% upper-tail. (b) p-values in parentheses; obtained using bootstrap with 1000 replications.

Table 5 presents symmetry tests with respect to the origin of price shocks. For all quantile levels considered, soybeans have been a net transmitter of price risk to meal and oil. Therefore, although (on the basis of Table 2) there is statistically significant information transmission upstream as well as downstream, the intensity at which information is transmitted is likely to be higher from the input to the final products' markets than the other way round. The derived demand theory (Marshall, 1920) predicts the opposite (that means, prices are first established at the final product markets, and they are transmitted subsequently upstream to the intermediate good markets). According to Adrangi *et al*. (2006), a pattern of information flow contrary to the predictions of derived demand theory may arise when the market structure changes along a continuum of vertically interrelated markets. For the US soybean complex, in particular, soybean processing is populated by several major operators (among them are Archer Daniels Midland Co, Bungle Limited, and Cargil Incorporated). As such, soybean processing may be thought of as oligopolistic/oligopolistic. Downstream, wholesaling and retailing tend to be more competitive.

Table 5: Symmetry Tests with Respect to the Origin of Price Shocks

(Ho: The origin of price shocks does not matter for the intensity of transmission)

Differences	5% lower	Median	5% upper
	Empirical value	Empirical value	Empirical value
(Meal® Soybeans) - (Soybeans® Meal)	-0.393 (0.078)	-0.640 (<0.01)	-0.294 (0.035)
Oil® Soybeans) - (Soybeans® Oil)	-0.924 (<0.01)	-1.121 (<0.01)	-0.627 (<0.01)
(Meal® Oil) - (Oil® Meal)	-0.046 (0.820)	-0.408 (<0.01)	-0.214 (0.078)

Note: (a) The empirical values are coefficient at the 5% lower-tail minus coefficient at the 5% upper-tail. (b) p-values in parentheses; obtained using bootstrap with 1000 replications.

In any case, vertical asymmetric transmission has important implications for the behaviour of the crush spread. An increase in soybeans price by 1% is likely to increase the final product's price (at the 5%

lower and the median quantile thresholds) by more than 1% working, towards widening the spread[8]. Exactly the same (i.e., widening of the spread), however, will be the case (at all quantile thresholds, again) when the prices of oil and meal increase by 1%. Therefore, soybean processors appear to have an advantage both downstream (over wholesalers and retailers) and upstream (over farmers). For the horizontal transmission, shocks from meal to oil (at the median and the upper-tail) are transmitted with higher intensity relative to those in the opposite direction.

4. Conclusions and Future Research

The objective of the present work has been to investigate price linkages in the US soybean complex. This has been pursued using daily futures prices from 2015 to 2023 and a flexible econometric approach that allows modelling simultaneously both vertical and horizontal linkages at different parts of the joint distribution.

The empirical results suggest:

a) There are strong and positive vertical price linkages between soybean and its products both under large (in absolute value terms) and small price shocks. The intensity of information transmission, however, is higher downstream suggesting that (in contrast to the theory of derived demand) price changes in the soybean complex in the US are more likely to be established in the soybean market than in the meal and the oil markets. This pattern of vertical price transmission is consistent with a widening of the crush spread under shocks emanating from either the input or the final products' markets. It further indicates that processors may possess market power relative to firms operating at different levels of the complex and (for the purposes of price risk management) may make the evolution of crush spread more predictable.
b) The meal and oil prices are unconnected under large negative shocks and exhibit an inverse relationship at the median and the upper extremes. This is a direct result of their joint production in fairly fixed proportions. Given that in recent years there is a strong demand for soybean oil in the biodiesel industry, the "crushing for oil" is likely to benefit livestock producers and harm producers of substitute feedstocks such as corn silage, cottonseed meal, citrus pulp, etc.
c) Price risk transmission across all three quantile thresholds considered is asymmetric. Generally, the futures prices are more strongly connected around the median relative to the extremes of the joint distribution. A possible explanation for this finding is that market-specific factors such as the supply of the main international competitors or the global demand set a limit to the ability of domestic producers to pass very large (in absolute value terms) price shocks from one market of the complex to the others.
d) The existence of quantile-dependent linkages, along with the non-positive association between soybean meal and soybean oil prices, facilitate speculation and point to limited potential for "self-hedged" profit. It appears that soybean processors may have better, as a risk-minimising strategy, employ simple equal and opposite hedges on individual commodities in the complex.

Future works may enrich the empirical analysis by allowing for asymmetric price risk transmission, not only across the quantiles of the joint distribution but across frequencies as well. Barunik and Kley (2019) showed that this is possible for bi-variate distributions. Market networks in the real world, however, typically involve multiple markets. Therefore, additional research on this elaborate topic is certainly warranted.

[8] This is evident from the sensitivity coefficients is Table 2.

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