A Multivariate Quantile Approach for Testing Asymmetric Price Transmission in a Joint Production Process

Yao Yang and Berna Karali [*]

Output markets usually respond to input price changes asymmetrically, with prices rising faster than they fall, known as the rockets and feathers pattern. This pattern has not been yet tested for a joint production process despite strong connections among markets. We fill this gap by using a vector error correction quantile framework and apply our model to soybean meal and oil, jointly produced by crushing soybeans. We find output prices respond more to input price increases when their own market is bullish but the other market is bearish, confirming the rockets and feathers pattern at the extremes of price distributions.

Key words: asymmetric price response, rockets and feathers, quantile cointegration, soybean crush, vertical price transmission

"Prices rise like rockets but fall like feathers." —Mariano Tappata (Tappata 2009)

Introduction

Price is one of the mechanisms to transmit shocks among markets linked through the supply chain. A well-known empirical finding is that output prices do not symmetrically react to the changes in input prices, with output prices rising faster than they fall, termed as the "rockets and feathers" pattern (Bacon 1991). For instance, retail gasoline prices rise quickly as crude oil prices increase, but pump prices remain high even as crude oil prices fall.[1] While Peltzman (2000) finds the prevalence of price asymmetry in more than 250 product categories, other researchers have pointed out the challenges in econometric modeling for testing price asymmetry.[2]

Previous theoretical and empirical studies consider the production process for a single output.[3] But, many raw materials or products can be processed into more than one output. While

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[1] An extensive literature explains price asymmetries by market power (e.g., McCorriston, Morgan, and Rayner 2001; Weldegebriel 2004; Antonova 2013; Bulutay et al. 2021), adjustment costs (e.g., Barro 1972; Buckle and Carlson 2000), search costs (e.g., Tappata 2009; Lewis 2011), government intervention (e.g., Kinnucan and Forker 1987), and inventory or stock management (e.g., Blinder 1982).

[2] For example, the presence of structural breaks leads to the over-rejection of the null hypothesis of price symmetry in Peltzman's study (von Cramon-Taubadel and Meyer 2001), and the failure to account for the characteristics of price series can bias the results of asymmetry tests (Tifaoui and von Cramon-Taubadel 2017).

[3] Although not in the context of vertical price transmission, two previous studies investigate the implications of joint production on price elasticities of demand. Houck (1964) theoretically shows the price elasticity of a raw agricultural product as the harmonic average of the price elasticities of the jointly-produced end

extensive literature has examined asymmetric price transmission across farm, wholesale, and retail markets for various commodities, such as beef, pork, and salmon (e.g., Goodwin and Holt 1999; Miller and Hayenga 2001; Bonnet and Villas-Boas 2016), the joint production feature of some of these agricultural commodities have been ignored. von Cramon-Taubadel and Goodwin (2021) point out that price (or volatility) transmission from an input to one of its end products can be affected by the prices of other outputs because of strong connections among the markets; and therefore, the estimation equations for price asymmetry might be misspecified when one ignores the other output's price levels. As the authors state in their review of price transmission in agricultural markets, the issue of vertical price transmission in joint production has only been touched upon in the literature and the standard practice has been to associate the price of an upstream product with the price of only one of the downstream products by ignoring the interrelationships among the outputs (e.g., Kinnucan and Forker 1987; von Cramon-Taubadel 1998; Serra and Goodwin 2003).[4]

Our study fills this gap in the empirical literature and contributes to the asymmetric price transmission literature both contextually and methodologically. To the best of our knowledge, our study is the first to test for asymmetric price transmission in a *joint production process* and to allow output price responses to *vary* with the prices of other end products. While Borenstein, Cameron, and Gilbert (1997) consider the possible impact of heating oil prices in their study of gasoline price responses to crude oil price changes, they do not take into account the long-run relationships between these products. On the theoretical side, Antonova (2013) derives elasticities of vertical price transmission in joint production and points out that the differences in the price transmission of jointly-produced products depend on the independent demands for those goods. Even though her study is the first attempt to investigate the theoretical aspects of price transmission for jointly-produced outputs, it falls short of providing an empirical application of the theoretical results and leaves it as a future work. We take up this task and provide the first empirical test of price asymmetry in a joint production process. We accomplish this through a multivariate *quantile* framework that provides flexibility in allowing output price responses in the short-run to depend on each other.[5] Specifically, we investigate price responses for every possible pair of the quantile indices of output prices. As a result, we test for price asymmetry in the end products of a joint production process across the entire distribution and provide a comprehensive picture of locations where asymmetry occurs.

As an application, we choose the soybean complex (soybean, soybean meal, and soybean oil) because soybean crushing is a relatively well-defined joint production with fixed proportions. We find evidence of rockets and feathers patterns (i.e., positive price asymmetry) in the soybean complex when the realizations of soybean end products are in the opposite extreme deciles of their price change distributions. This finding suggests that a positive price asymmetry in jointly produced commodities might exist when one market is bullish whereas the other is bearish. Thus, producers are more likely to pass extra production costs onto consumers when there is a high demand for one of the end products (bullish sentiment) and a low demand for the other end product (bearish sentiment). This could happen when the end products have unrelated demand drivers. Because soybean meal and oil are consumed for different purposes (animal feed for soybean meal; cooking oil and biodiesel for soybean oil), their demands often change independently of each other (Dronne and Tavéra 1988; United Soybean Board 2019). In fact, in recent years the demand

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products. Piggott and Wohlgenant (2002) expand on Houck's model and allow for the possibility of trade of both the raw product and its joint outputs.

[4] In addition to von Cramon-Taubadel and Goodwin (2021), Meyer and von Cramon-Taubadel (2004) and Frey and Manera (2007) also provide excellent reviews on the possible reasons for price asymmetry and econometric methods used in the literature to identify price asymmetry.

[5] In the case of a single production process, extensive literature empirically tests price asymmetry by threshold autoregressive models (e.g., Goodwin and Holt 1999; Richards, Gómez, and Lee 2014), error correction models (e.g., von Cramon-Taubadel 1998), and asymmetric multivariate generalized autoregressive conditional heteroskedasticity models (e.g., Abdelradi and Serra 2015).

for soybean oil, and hence its price, surged due to increased demand for biodiesel, the vegetable oil shortages out of Ukraine, and drought conditions in South America and Canada, leading to an oversupply of soybean meal and thereby reducing meal price (Ates and Bukowski 2022; Lusk 2022). Our study shows that asymmetric price transmission might emerge as a pricing strategy in such cases. Thus, our study not only empirically tests price asymmetry in a joint production process for the first time, but also provides an econometric tool for a comprehensive analysis of price asymmetry that takes into account the dependence of output responses on each other.

Methods

To explore whether the occurrence of price asymmetry varies by the market conditions of the other jointly-produced output, we expand on the multivariate quantile autoregressive (VARQ) model of Montes-Rojas (2019) by incorporating quantile cointegrating relationships. A similar extension of a standard quantile autoregressive model has been applied by Burns and Kane (2022) in the crude oil futures markets by taking the first differences and including an error correction term. In this section, we first briefly discuss how we test for cointegration in the soybean complex and how we base our model on the weak exogeneity of soybean prices, and then we introduce a bivariate vector error correction quantile (VECQ) model for soybean end products: soybean meal and soybean oil.

Cointegration tests

Testing for cointegrating relationships among price series is necessary to avoid spurious correlations among non-stationary data. Moreover, soybean meal and oil are jointly produced in a fixed proportion when crushing soybeans. As a result, the price series of the soybean complex is expected not to drift too far apart in the long run.[6]

We denote the τ_i quantile of log price of commodity i at time t, $p_{i,t}$, as $q_{p_{i,t}}(\tau_i)$, where $i = M$ (soybean meal), O (soybean oil), and S (soybean). The vector $\mathbf{p}_{-i,t} = (\dots, p_{i-1,t}, 0, p_{i+1,t}, \dots)'$ includes all prices excluding commodity i and $\Delta\mathbf{p}_{-i,t} = (\dots, \Delta p_{i-1,t}, 0, \Delta p_{i+1,t}, \dots)'$ is the corresponding first differences. We use the augmented quantile regression (Xiao 2009) to investigate the cointegrating relationships at different conditional quantiles, $q_{p_{i,t}}(\tau_i|\mathbf{p}_{-i,t})$, as follows:

(1)
$$q_{p_{i,t}}(\tau_i|\mathbf{p}_{-i,t}) = \alpha + \boldsymbol{\beta}'\mathbf{p}_{-i,t} + \sum_{j=-J}^{J} \Delta\mathbf{p}'_{-i,t-j}\,\boldsymbol{\pi}_j + F_\varepsilon^{-1}(\tau_i),$$

where $F_\varepsilon^{-1}(\tau_i)$ is the inverse cumulative distribution function of the residuals for each commodity i.[7] The cointegrating relationships can be tested based on the quantile regression residual as $\varepsilon_{\tau_i,t} = p_{i,t} - q_{p_{i,t}}(\tau_i|\mathbf{p}_{-i,t})$.[8]

We follow the Engle-Granger two-step method to identify the existence of cointegrating relationships by examining whether the residuals from the conditional quantiles are stationary or not. We select nine quantile indices evenly located in the price distribution of each commodity

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[6] Dronne and Tavéra (1988) theoretically derive a cointegrating relationship among these three commodities by maximizing the long-run profit of soybean processors and provide empirical evidence for such a long-run equilibrium relationship using the two-step cointegration test of Engle and Granger (1987). In addition, Simanjuntak et al. (2020) examine the international prices provided by the Food and Agriculture Organization and find evidence of cointegration in the soybean complex.

[7] Parameters α, $\boldsymbol{\beta}'$, $\boldsymbol{\pi}_j$ are functions of quantile index τ_i, and each varies across different quantiles of $p_{i,t}$ distribution. We omit the subscripts for the quantile index in the equation for a clear exposition.

[8] In our empirical analysis, the number of leads and lags, J, is two based on the Akaike information criterion.

from 0.1 to 0.9 and show that prices are cointegrated at these selected quantile indices, necessitating the inclusion of error correction terms in the VARQ model.

Weak exogeneity tests

Because our main focus is on the asymmetric responses in output prices following a change in the input price, we are solely interested in modeling the output price equations. However, this requires the exogeneity of soybean prices. In fact, Ericsson (1992) argues that the exogeneity assumption of the nuisance variables permits simpler modelling strategies and reduces computational complexities in a cointegrated system. Therefore, we first demonstrate that soybean prices could be treated as weakly exogenous, allowing us to build a bivariate VECQ model with only soybean end products. We explain these tests in detail and present their results in appendix A.

Testing for asymmetric price responses based on conditional quantiles

Quantile regression, introduced by Koenker and Bassett (1978), expands the least squares estimation for conditional means to quantile estimation for conditional quantiles over the entire distribution of the dependent variable. The application of univariate quantile regression to price series provides more flexible modeling options for risk management and asymmetric price dynamics (e.g., Engle and Manganelli, 2004; Laporta, Merlo, and Petrella, 2018).[9]

Extending the univariate quantile framework to a multivariate one is complicated because the lack of a natural ordering of a multidimensional Euclidean space leads to a loose definition of multivariate quantiles (Serfling 2002). Hallin, Paindaveine, and Šiman (2010) point out a close conceptional kinship between the quantile and depth, and bridge the gap between these two concepts to provide a hyperplane-based definition of multivariate quantiles and define multivariate quantiles of a random vector as directional objects.[10,11] Montes-Rojas (2019) applies this definition of multivariate quantiles to generalize the univariate quantile autoregressive regression proposed by Koenker and Xiao (2006) to a multivariate framework and develops a VARQ model. The VARQ model simultaneously solves a system of univariate quantile autoregressive models since the directional quantiles are univariate regression quantiles for a fixed orthonormal basis (Montes-Rojas 2017).

More specifically, we first set up directional quantiles of each component in a vector at time *t* conditioning on its lags and exogenous variables, and then simultaneously solve a system of conditional directional quantile functions. We further consider the cointegrating relationships among price series and augment the VARQ model with error correction terms to build a VECQ model.

To capture the asymmetric responses of output prices to input price changes we segment $\Delta p_{S,t-j}$ into increasing and decreasing parts, $\Delta p_{S,t-j}^+ = max(\Delta p_{S,t-j}, 0)$ and $\Delta p_{S,t-j}^- =$

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[9] Univariate quantile methods are used in studies on the price dynamics in energy markets (Schweikert 2019), the impacts of public and private stocks on prices in corn and wheat markets (Chavas and Li 2020), the farm-retail price relationship in the presence of the pork cycle (Chavas and Pan 2020; Chavas 2021), and the movements in futures and spot prices (Huang, Serra, and Garcia 2020).

[10] Another method for modeling multivariate quantiles, for instance, is to factorize the joint distribution in a recursive structure (Chavleishvili and Manganelli 2019) or to combine univariate quantile autoregressions via a copula function (Li and Chavas 2023).

[11] More specifically, Hallin, Paindaveine, and Šiman (2010) defines the multivariate quantiles of a random vector $\mathbf{Y} = (y_1, \dots, y_m)'$ as directional objects: $m - 1$ dimensional hyperplanes indexed by vectors $\boldsymbol{\tau}$ ranging over the open unit ball of $\mathbb{R}^m$. The $\boldsymbol{\tau}$ quantile of $\mathbf{Y}$ is defined as the τ-quantile hyperplane of regressing $\mathbf{u}'\mathbf{Y}$ on the marginals of $\boldsymbol{\Gamma}_u'\mathbf{Y}$ and a constant, where Γ_u is an arbitrary $m \times (m-1)$ matrix representing an orthonormal basis of the vector space orthogonal to $\mathbf{u}$.

$min(\Delta p_{S,t-j}, 0)$. After we identify cointegrating relationships, we denote $\mathbf{X}_t = (\Delta \mathbf{w}'_{t-1}, \mathbf{Z}'_t)'$, where $\mathbf{w}_t = (p_{M,t}, p_{O,t})'$, $\mathbf{Z}_t = (\widehat{EC}_{t-1}, \sum_{j=0}^{J} \Delta p^+_{S,t-j}, \sum_{j=0}^{J} \Delta p^-_{S,t-j})'$, and $\widehat{EC}_{t-1}$ are the estimated quantile cointegrating relationships defined in equation (1) among the price series at different multivariate quantiles $\mathbf{v} = (\tau_M, \tau_O)'$ with τ_M and τ_O representing quantile indices of soybean meal and oil, respectively.[12] We then write the directional quantiles as follows:

(2) $\{\boldsymbol{\gamma}(\tau_i, \mathbf{d}, \boldsymbol{\Gamma}_d)', \boldsymbol{\theta}(\tau_i, \mathbf{d}, \boldsymbol{\Gamma}_d)', \alpha(\tau_i, \mathbf{d})\}' \equiv \arg\min \mathrm{E}\{\rho_{\tau_i}(\mathbf{d}'\Delta \mathbf{w}_t - \boldsymbol{\kappa}'\boldsymbol{\Gamma}_d'\Delta \mathbf{w}_t - \boldsymbol{\theta}'\mathbf{X}_t - \alpha)\}$,

where $\mathbf{d}$ is a directional vector of any one of the soybean end products and $\boldsymbol{\Gamma}_d$ is a directional vector of the other product. $\rho_{\tau_i}(\varepsilon) = \varepsilon(\tau_i - I(\varepsilon < 0))$, $\forall \varepsilon \in \mathbb{R}$, is the loss function, where $I(\cdot)$ is an indicator that is equal to one if the statement in the parenthesis is correct and zero otherwise, and α represents a constant. With a fixed orthonormal basis $(\mathbf{d}, \boldsymbol{\Gamma}_d)$, and a given multivariate quantile $\mathbf{v}$, the system of two conditional quantile functions can be written as,

(3) $q_M(\mathbf{v}|\mathbf{X}_t) = \kappa_M(\tau_M)q_O(\mathbf{v}|\mathbf{X}_t) + \sum_{\ell=1}^{\mathcal{L}} \mathbf{a}_{M\ell}(\tau_M)'\Delta \mathbf{w}_{t-\ell} + \sum_{j=0}^{J} b^+_{Mj}(\tau_M)\Delta p^+_{S,t-j}$

$$+ \sum_{j=0}^{J} b^-_{Mj}(\tau_M)\,\Delta p^-_{S,t-j} + c_M(\tau_M)\widehat{EC}_{t-1} + \mu_M(\tau_M) + \varepsilon_{M,t}(\tau_M),$$

$$q_O(\mathbf{v}|\mathbf{X}_t) = \kappa_O(\tau_O)q_M(\mathbf{v}|\mathbf{X}_t) + \sum_{\ell=1}^{\mathcal{L}} \mathbf{a}_{0\ell}(\tau_O)'\Delta \mathbf{w}_{t-\ell} +$$

$$\sum_{j=0}^{J} b^+_{Oj}(\tau_O)\,\Delta p^+_{S,t-j}$$

$$+ \sum_{j=0}^{J} b^-_{Oj}(\tau_O)\,\Delta p^-_{S,t-j} + c_O(\tau_O)\widehat{EC}_{t-1} + \mu_O(\tau_O) + \varepsilon_{o,t}(\tau_O).$$

Note that our model allows for asymmetry only in the short-run output price responses to soybean price shocks while the long-run relationship and short-run output price effects are symmetric.

To simultaneously solve the equations in the above system, we rewrite the coefficients in vectors and matrices as follows:

(4) $\mathbf{q}_{\Delta \mathbf{w}_t}(\mathbf{v}|\mathbf{X}_t) = (q_M(\mathbf{v}|\mathbf{X}_t), q_O(\mathbf{v}|\mathbf{X}_t))'$,

$$\boldsymbol{\kappa}(\mathbf{v}) = (\kappa_M(\tau_M), \kappa_O(\tau_O))', \quad \mathbf{a}(\mathbf{v}) = \begin{bmatrix} a_{M1}(\tau_M) & \cdots & a_{M\mathcal{L}}(\tau_O) \\ a_{01}(\tau_O) & \cdots & a_{0\mathcal{L}}(\tau_O) \end{bmatrix},$$

$$\mathbf{b}^+(\mathbf{v}) = \begin{bmatrix} b^+_{M0}(\tau_M) & \cdots & b^+_{MJ}(\tau_M) \\ b^+_{O0}(\tau_O) & \cdots & b^+_{OJ}(\tau_O) \end{bmatrix}, \quad \mathbf{b}^-(\mathbf{v}) = \begin{bmatrix} b^-_{M0}(\tau_M) & \cdots & b^-_{MJ}(\tau_M) \\ b^-_{O0}(\tau_O) & \cdots & b^-_{OJ}(\tau_O) \end{bmatrix},$$

$$\mathbf{c}(\mathbf{v}) = \begin{bmatrix} c_M(\tau_M) \\ c_O(\tau_O) \end{bmatrix}, \quad \boldsymbol{\mu}(\mathbf{v}) = \begin{bmatrix} \mu_M(\tau_M) \\ \mu_O(\tau_O) \end{bmatrix}, \text{ and } \boldsymbol{\varepsilon}_t(\mathbf{v}) = \begin{bmatrix} \varepsilon_{M,t}(\tau_M) \\ \varepsilon_{O,t}(\tau_O) \end{bmatrix}.$$

Following Montes-Rojas (2019), the reduced-form VECQ model is defined as:

(5) $\mathbf{q}_{\Delta \mathbf{w}_t}(\mathbf{v}|\mathbf{X}_t) = \{\mathbf{I}_2 - \boldsymbol{\kappa}(\mathbf{v})\}^{-1} \left\{ \mathbf{a}(\mathbf{v}) \begin{bmatrix} \Delta \mathbf{w}'_{t-1} \\ \vdots \\ \Delta \mathbf{w}'_{t-\mathcal{L}} \end{bmatrix} + \mathbf{b}^+(\mathbf{v}) \begin{bmatrix} \Delta p^+_{S,t} \\ \vdots \\ \Delta p^+_{S,t-J} \end{bmatrix} + \mathbf{b}^-(\mathbf{v}) \begin{bmatrix} \Delta p^-_{S,t} \\ \vdots \\ \Delta p^-_{S,t-J} \end{bmatrix} \right\}$,
$$+ \mathbf{c}(\mathbf{v})\widehat{EC}'_{t-1} + \boldsymbol{\mu}(\mathbf{v}) + \boldsymbol{\varepsilon}_t(\mathbf{v})$$

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[12] In our empirical application, following Balke and Fomby (1997), we test for structural breaks in the equilibrium error. Any such break would imply a discontinuity in the adjustment process to the long-run equilibrium. We find no statistical evidence for a structural break, suggesting that a linear cointegration model rather than threshold cointegration is appropriate.

where $\mathbf{I_2}$ is a 2×2 identity matrix. Therefore, the price responses of soybean end products to soybean price increases are

$$(6) \qquad \mathbf{B}^+(\mathbf{v}) := \{\mathbf{I_2} - \mathbf{\kappa}(\mathbf{v})\}^{-1}\mathbf{b}^+(\mathbf{v}) = \begin{bmatrix} B_{M0}^+(\mathbf{v}) & ... & B_{MJ}^+(\mathbf{v}) \\ B_{O0}^+(\mathbf{v}) & ... & B_{OJ}^+(\mathbf{v}) \end{bmatrix},$$

and the price responses to soybean price decreases are

$$(7) \qquad \mathbf{B}^-(\mathbf{v}) := \{\mathbf{I_2} - \mathbf{\kappa}(\mathbf{v})\}^{-1}\mathbf{b}^-(\mathbf{v}) = \begin{bmatrix} B_{M0}^-(\mathbf{v}) & ... & B_{MJ}^-(\mathbf{v}) \\ B_{O0}^-(\mathbf{v}) & ... & B_{OJ}^-(\mathbf{v}) \end{bmatrix}.$$

In addition, the adjustment speeds, $\mathbf{C}(\mathbf{v}) := \{\mathbf{I_2} - \mathbf{\kappa}(\mathbf{v})\}^{-1}\mathbf{c}(\mathbf{v})$, measure how quickly the prices adjust when they depart from the long-run equilibrium.

We focus on the coefficients on soybean price changes from (6)-(7) to test price asymmetry for short-run responses of soybean end products. The cumulative price response of output i, $i = M, O$, to an increase in the soybean price at different multivariate quantiles $\mathbf{v}$ is

$$(8) \qquad \lambda_i^+(\mathbf{v}) = \sum_{j=0}^{J} B_{ij}^+(\mathbf{v}),$$

and the cumulative response to a decrease in the soybean price is

$$(9) \qquad \lambda_i^-(\mathbf{v}) = \sum_{j=0}^{J} B_{ij}^-(\mathbf{v}).$$

The difference between these responses, $\lambda_i = \lambda_i^+(\mathbf{v}) - \lambda_i^-(\mathbf{v})$, can be used for testing asymmetric price transmission.[13] If the difference is statistically different from zero, this will suggest existence of asymmetric price responses and its magnitude will show the degree of the price asymmetry. If the sign of this difference is positive, there is a positive price asymmetry, where output prices respond more fully to a positive shock in soybean prices, an indication of the rockets and feathers pattern. Similarly, a negative sign indicates negative price asymmetry, where output prices respond more to a negative shock in soybean prices.

Data

We use monthly cash prices from January 1984 to January 2020 obtained from Barchart (formerly, Commodity Research Bureau Trader) representing input (soybean—#1 yellow, Central Illinois,) and output (soybean meal—48% protein, Decatur, Illinois— and soybean oil—crude, Decatur, Illinois) prices.[14] Typically, one bushel of soybeans is about 60 pounds, which yields 48 pounds of soybean meal (with 44% protein content), 11 pounds of soybean oil, and one pound of waste.[15] When soybean meal and oil prices are converted to dollars per bushel, they account for the difference in yield from one bushel of soybeans and represent their crush value (Irwin 2017). As shown in Figure 1(a), soybean meal is more highly valued end product of soybeans on a per bushel basis. In contrast, when the difference in the yield is not taken into account, soybean oil is the more valued product on a per pound basis (Irwin 2017). Figure 1(b) displays the combined crush value of soybean meal and oil along with soybean prices. It is evident that the gap between the crush gross revenue and the input cost is wider at times, especially during the latter part of the sample.

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[13] In our empirical analysis, the number of lags, J, is one based on the Akaike information criterion.

[14] Illinois has been the largest soybean-producing state in the last five years. According to the National Agricultural Statistics Service, Illinois produced 672.64 million bushels of soybeans in 2021, followed by Iowa with 621.86 million bushels and Minnesota with 356.26 million bushels. Therefore, Illinois prices can be regarded as representative of the U.S. soybean crushing industry.

[15] These conversion factors are published by the U.S. Soybean Export, available at
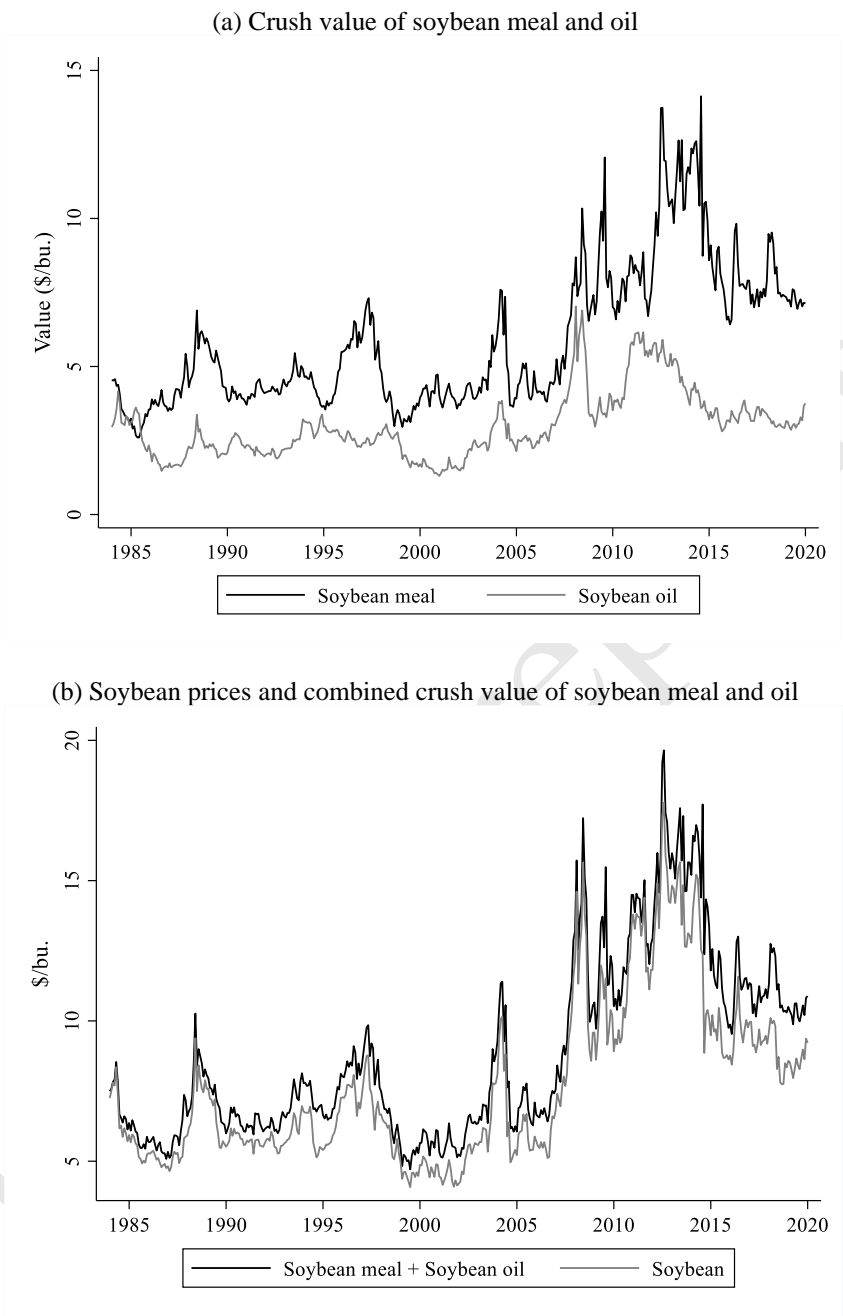https://ussec.org/resources/ conversion-table/.

(a) Crush value of soybean meal and oil

(b) Soybean prices and combined crush value of soybean meal and oil

Figure 1. Prices of the Soybean Complex

Table 1. Summary Statistics of Log Prices and Their First Differences in the Soybean Complex

	$p_{i,t} = ln(P_{i.t})$			$\Delta p_{i,t} = ln(P_{i,t}) - ln(P_{i,t-1})$		
	M	**O**	**S**	**M**	**O**	**S**
Mean	1.70	1.03	1.98	0.00	0.00	0.00
Std. dev.	0.37	0.35	0.35	0.09	0.07	0.07
Min	0.96	0.27	1.41	-0.48	-0.31	-0.40
Max	2.65	1.95	2.88	0.30	0.25	0.20
Skewness	0.45	0.27	0.55	-0.59	-0.21	-1.04
Kurtosis	2.24	2.78	2.35	7.05	4.72	6.82
Observations	433	433	433	433	433	433
ADF test	-2.16	-2.31	-2.12	-15.22***	-9.79***	-9.71***
Normality	25.14***	6.11***	29.34***	321.60***	56.67***	341.00***
Ljung-Box	807.17***	1895.08***	1562.78***	8.99***	9.00*	12.89***

Notes: The variables $p_{i,t}$ and $\Delta p_{i,t}$ represent the natural logarithm of cash prices and their first differences for each commodity i, where $i = M$ (soybean meal), O (soybean oil), and S (soybean). ADF test is the augmented Dickey-Fuller stationarity test with the null hypothesis of a unit root. Normality represents the Jarque-Bera test with the null hypothesis of normally distributed series. Ljung-Box is the autocorrelation test with the null hypothesis of independently distributed series. The ADF and the Ljung-Box tests are conducted based on the optimal lag for each series chosen by the Akaike information criterion (two for soybean meal, five for soybean oil, and four for soybeans). The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 1 reports summary statistics of log prices and their first differences.[16] All log price series have platykurtic distributions with positive skewness, indicating the right sides of price distributions are fatter. Soybean log prices are more skewed to the right than the other two commodities. On the other hand, the first-differenced log prices (i.e., returns) are negatively skewed and have leptokurtic distributions, indicating log price series are heavy tailed compared to normal distribution. Moreover, Jarque-Bera tests reject the normality of both log prices and their first differences, suggesting asymmetry in these distributions. Augmented Dickey-Fuller tests show that stationarity in log prices is achieved through first differencing, and Ljung-Box tests reject the null hypothesis of no autocorrelation in all series. In addition, based on the supremum Wald test we find no structural breaks during our sample period.[17]

Empirical Results

Quantile cointegration test results are presented in Table 2. We report the augmented Dickey-Fuller (ADF) test statistics for a unit root in the estimated residuals of three log price series based on equation (1). We reject the null hypothesis of a unit root at the 5% level or lower for each commodity, indicating that log prices are cointegrated at these selected quantile indices. Therefore, we augment the VARQ model of Montes-Rojas (2019) by including error correction terms to capture the adjustment speed when log prices depart from the long-run equilibrium and

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[16] The first-differenced log prices also represent returns. We use returns, first-differenced log prices, and log price changes interchangeably throughout the article.

[17] The supremum Wald statistic is 12.81 with a *p*-value of 0.27 for soybeans, 15.15 with a *p*-value of 0.14 for soybean meal, and 6.67 with a *p*-value of 0.90 for soybean oil.

Table 2. Tests for Cointegrating Relations at Selected Quantile Indices

| | τ_i | | | | | | | | |
	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
$p_{M,t}$	-4.26	-4.53	-3.79	-3.88	-3.87	-3.47	-3.30	-3.52	-4.38
$p_{O,t}$	-4.72	-6.22	-5.94	-5.53	-5.85	-5.36	-4.67	-4.18	-5.67
$p_{S,t}$	-4.72	-4.33	-4.00	-3.87	-3.63	-4.56	-4.26	-4.62	-5.04

Notes: Cointegration is tested via the augmented Dickey-Fuller (ADF) stationarity tests of the estimated residuals from equation (1) for a given quantile index τ_i, where $i = M$ (soybean meal), O (soybean oil), and S (soybean). The ADF statistics shown in regular (bold) font are statistically significant at the 1% (5%) level.

estimate our VECQ model. Moreover, as shown in appendix A, the weak exogeneity assumption of soybean prices (in log form) is satisfied across selected multivariate quantiles and therefore we treat soybean as exogenous and use the bivariate VECQ model in equation (5) to test for asymmetric output price responses.

All coefficients in (5) vary across different quantiles of both soybean meal and oil return distributions and using multivariate quantile $\mathbf{v} = (\tau_M \in (0.1, \dots, 0.9), \tau_O \in (0.1, \dots, 0.9))'$ leads to 81 estimates for each coefficient. This makes presenting and interpreting the results challenging as the pattern of price movements could be affected from two different directions, either its own quantiles or quantiles of the other product. For example, a 1% soybean price increase leads to a 1.04% contemporaneous increase in the soybean meal price when its own quantile index, τ_M, and the quantile of soybean oil, τ_O, are both 0.1. The same input price increase, on the other hand, leads to a 1.26% contemporaneous increase in the soybean meal price when τ_M increases to 0.9 and τ_O stays at 0.1, and to a 0.90% increase when τ_M stays at 0.1 and τ_O increases to 0.9. For brevity, we present the results from the VECQ model at only 0.1, 0.5, and 0.9 quantiles of both soybean meal and oil to represent extremely low, median, and extremely high levels, respectively, in Tables 3 and 4.[18] Since our main objective is to test for asymmetric output price responses to input price changes in the short run to infer existence of the rockets and feathers pattern, we only provide coefficient estimates on the soybean log price change variables in the tables.[19] Soybean prices have both contemporaneous and lagged effects on the prices of its end products. Therefore, the cumulative price response of the end products to soybean price changes are the sum of the coefficients on the current and lagged changes in the soybean log price. We report those cumulative price responses and the test results for price asymmetry (the difference between cumulative responses to positive and negative input price changes) in Tables 3 and 4.[20] For a comparison, we also provide the associated estimates from a standard vector error correction (VEC) model, which focuses on conditional means, in the last columns of both tables.[21]

The contemporaneous effects in VECQ are statistically significant at the 1% level for both soybean meal (Table 3) and soybean oil (Table 4) except for the soybean oil response to a negative change in the soybean log price at the high quantile. While the lagged effects are only statistically significant in the soybean meal market when its return is at the median quantile, they are

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[18] Full results with fixed quantiles from 0.1 to 0.9 are available from the authors upon request.

[19] We do not discuss price adjustment speeds towards the long-run equilibrium in our study but report the estimated coefficients on the error correction term in equation (5) at each quantile from 0.1 to 0.9 in appendix Tables B.1 and B.2 for soybean meal and oil, respectively.

[20] While for brevity we present the results at only 0.1, 0.5, and 0.9 quantiles of soybean meal and oil, we provide the full results for the cumulative price responses and the test results for price asymmetry with fixed quantiles from 0.1 to 0.9 in appendix Tables C.1 and C.2.

[21] The corresponding tests of weak exogeneity and cointegration, and the full estimation results for the standard VEC model are available from the authors upon request. For comparison purposes, the selected estimation results for the VEC model are provided in Tables 3 and 4 and in the notes to Tables B.1 and B.2.

Table 3. VECQ Results for Soybean Meal Responses

	VECQ						VEC	
				τ_M				
	0.1		**0.5**		**0.9**		**VEC**	
$\Delta p_{S,t}^+$	0.918	***	0.952	***	1.130	***	1.015	***
	(0.199)		(0.098)		(0.205)		(0.067)	
$\Delta p_{S,t}^-$	1.063	***	0.949	***	0.843	***	0.951	***
	(0.147)		(0.074)		(0.163)		(0.052)	
$\Delta p_{S,t-1}^+$	0.381		0.333	*	0.109		0.214	*
	(0.267)		(0.196)		(0.264)		(0.112)	
$\Delta p_{S,t-1}^-$	0.673	***	0.379	**	-0.313		0.169	
	(0.198)		(0.180)		(0.253)		(0.098)	
Cumulative price response:								
λ_M^+	1.299	***	1.285	***	1.240	***	1.229	***
	(0.285)		(0.221)		(0.332)		(0.155)	
λ_M^-	1.736	***	1.328	***	0.530	*	1.120	***
	(0.259)		(0.178)		(0.297)		(0.140)	
λ_M	-0.436		-0.043		0.710	*	0.109	
	[0.120]		[0.831]		[0.065]		[0.386]	

Notes: The estimated coefficients on soybean price changes are presented for soybean meal from the VECQ model, in which the soybean oil quantile τ_O is fixed at 0.5 and soybean meal quantile τ_M is varied between 0.1, 0.5, and 0.9. Standard errors are given in parentheses and *p*-values are in brackets. $\Delta p_{S,t-j}^+$ and $\Delta p_{S,t-j}^-$ denote, respectively, a positive and negative change in the soybean price, where $j = 0, 1$. λ_M^+ and λ_M^- represent the cumulative price response of soybean meal to soybean price increases and decreases, respectively. λ_M measures the difference between these two cumulative responses, $\lambda_M = \lambda_M^+ - \lambda_M^-$. The null hypothesis of symmetry in output price responses is $\lambda_M = 0$. For a comparison, corresponding results from the standard VEC model are presented in the last column. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

significant in the soybean oil market when its log price changes are at the 0.9 quantile. For soybean meal, the cumulative price response to soybean price changes is statistically significant at each selected quantile (Table 3). Even though the cumulative price response to a 1% increase in soybean prices is smaller compared to a 1% decrease at the low and median quantiles (1.30% vs 1.74% at the 0.1 quantile and 1.29% vs 1.33% at the 0.5 quantile), their differences are not statistically different from zero (*p*-values of 0.120 and 0.831 for λ_M). However, there is a positive price asymmetry at the extremely high quantile, statistically significant at the 10% level, with soybean meal prices reacting more fully (1.24%) to soybean price increases than they do to soybean price decreases (0.53%). Further, Table C.1 shows that the equality of cumulative price responses of soybean meal to soybean price changes is rejected 18 times out of 81 cases at the 10% level or lower (shaded cells). It is also worth mentioning that once the soybean oil quantile exceeds 0.5, price asymmetry in soybean meal becomes evident at its lower quantiles. The standard VEC model, on the other hand, finds statistically equivalent cumulative price responses to both positive (1.23%) and negative (1.12%) changes in soybean prices (a *p*-value of 0.39 for their difference, λ_M).

For soybean oil, the cumulative price responses are statistically significant at the extremely low quantile but their difference is statistically different from zero (at the 10% level) at the median and high quantile (see Table 4). Once again, the standard VEC model (Table 4) fails to reject the equality of price responses in soybean oil responses to soybean price changes with a *p*-value of 0.37. Thus, no price asymmetry can be found in either market based on the VEC model estimation, which focuses only on the conditional mean of price distributions. Table C.2 further demonstrates that in 30 out of 81 cases (shaded cells), there is statistical evidence of price

Table 4. VECQ Results for Soybean Oil Responses

	VECQ							
	τ_O							
	0.1		**0.5**		**0.9**		**VEC**	
$\Delta p_{S,t}^+$	0.756	***	0.996	***	1.029	***	0.841	***
	(0.182)		(0.146)		(0.158)		(0.083)	
$\Delta p_{S,t}^-$	0.833	***	0.556	***	0.311		0.581	***
	(0.127)		(0.097)		(0.197)		(0.082)	
$\Delta p_{S,t-1}^+$	-0.058		-0.345		-0.623	**	-0.273	*
	(0.298)		(0.231)		(0.286)		(0.154)	
$\Delta p_{S,t-1}^-$	0.098		-0.320	*	-0.746	***	-0.136	
	(0.380)		(0.190)		(0.261)		(0.144)	
Cumulative price response:								
λ_O^+	0.698	**	0.651	***	0.406		0.568	***
	(0.334)		(0.245)		(0.342)		(0.165)	
λ_O^-	0.931	**	0.236		-0.434		0.445	**
	(0.389)		(0.205)		(0.316)		(0.177)	
λ_O	-0.233		0.415	*	0.841	*	0.123	
	[0.512]		[0.088]		[0.055]		[0.373]	

Notes: The estimated coefficients on soybean price changes are presented for soybean oil from the VECQ model, in which the soybean meal quantile τ_M is fixed at 0.5 and soybean oil quantile τ_O is varied between 0.1, 0.5, and 0.9. Standard errors are given in parentheses and *p*-values are in brackets. $\Delta p_{S,t-j}^+$ and $\Delta p_{S,t-j}^-$ denote, respectively, a positive and negative change in the soybean price, where $j = 0, 1$. λ_O^+ and λ_O^- represent the cumulative price response of soybean oil to soybean price increases and decreases, respectively. λ_O measures the difference between these two cumulative responses, $\lambda_O = \lambda_O^+ - \lambda_O^-$. The null hypothesis of symmetry in output price responses is $\lambda_O = 0$. For a comparison, corresponding results from the standard VEC model are presented in the last column. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

asymmetry in the soybean oil responses, with the majority appearing at the lower quantiles of soybean meal. These results provide support to our argument that asymmetric price response in joint production might depend on market conditions of all outputs.

To further demonstrate this, we plot the results in Tables C.1 and C.2 for selected quantiles of the other end product. Specifically, we plot the cumulative price responses of one end product at its own quantile from 0.1 to 0.9 when the other end product's quantile is fixed at 0.1, 0.5, and 0.9 to represent extremely low, median, and extremely high levels, respectively. We present these cumulative price response patterns in Figure 2. The left panel in Figure 2 shows the cumulative price responses to soybean price increases estimated by (8), and the right panel shows the cumulative responses to soybean price decreases given by (9). We calculate the standard errors of the parameter estimates by bootstrapping (with resampling 500 times). In the figures, coefficient estimates that are statistically significant at the 10% level or lower are plotted with a filled marker symbol, while insignificant estimates are indicated with an open marker. In addition, for a comparison, the estimates of the cumulative coefficients, λ_i^+ and λ_i^- from the standard VEC model are shown by horizontal lines.

In Figure 2(a), all soybean meal cumulative price responses are positive and statistically significant at the 5% level or lower, except for soybean price decreases at $\tau_M = 0.9$ and $\tau_O = 0.1$. In the case of soybean price increases, regardless of the soybean oil quantile τ_O, the smallest price response always occurs at the 0.4 quantile while the largest one occurs at the 0.8 quantile of
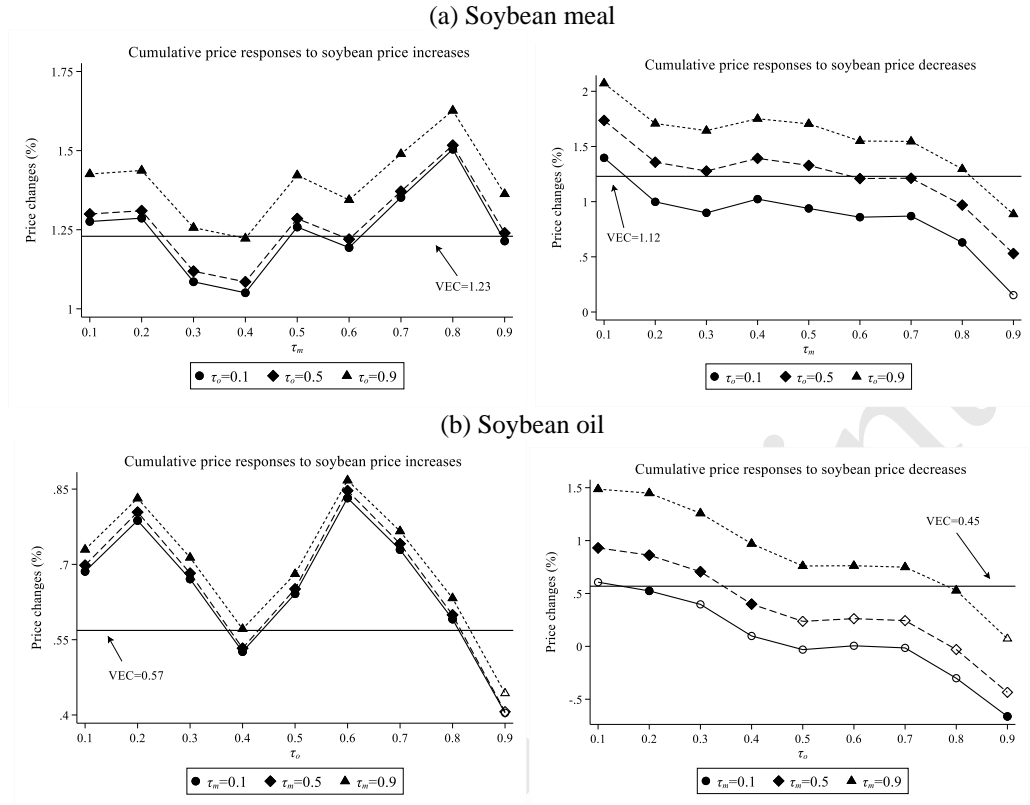
(a) Soybean meal

(b) Soybean oil

Figure 2. Output Price Responses to Soybean Price Changes

Notes: Cumulative price responses to soybean price increases and decreases are calculated as in equations (8) and (9), respectively. Coefficient estimates that are statistically significant at the 10% or lower level are plotted with a filled marker symbol, while insignificant estimates are indicated with an open marker. The horizontal lines represent the corresponding estimate from the standard VEC model.

soybean meal. Specifically, when the soybean oil return is in the highest decile of its distribution, the cumulative price response of soybean meal is 1.43% at $\tau_M = 0.1$, dips to 1.22% at $\tau_M = 0.4$, then reaches its peak of 1.63% at $\tau_M = 0.8$, and finally falls back to 1.36% at $\tau_M = 0.9$. This pattern also holds at the low and median quantiles of soybean oil. Compared to the VEC model estimate of 1.23%, which represents the cumulative price response of soybean meal to soybean price increases at the mean of price change distributions, all estimates in Figure 2(a) are larger when the soybean oil quantile is at 0.9, except for $\tau_M = 0.4$,. In addition, for a given soybean meal quantile τ_M, the meal price response is the largest when the soybean oil price is at its highest decile, while at the same time the responses are almost the same at the lowest and median quantiles of oil. Considering the case of soybean price decreases, the largest cumulative price response of soybean meal occurs at $\tau_M = 0.1$, followed by a slightly downward trend as its own quantile increases, regardless of the soybean oil quantile. Again, the soybean meal price responses are larger in magnitude when the other end product, soybean oil, is at a high quantile. Comparing to the VEC model estimate of λ_M^-, given by the horizontal line, price responses estimated by the VECQ model are far above at extremely low quantile of soybean meal, especially when the soybean oil quantile τ_O is high. Specifically, at $\tau_M = 0.1$ and $\tau_O = 0.9$, the cumulative meal price response to a 1% decrease in soybean price is 2.07% compared to the VEC model estimate of 1.12%.

In Figure 2(b), regardless of the soybean meal quantile, all cumulative soybean oil price responses to increases in the soybean price are also positive, but the response is statistically insignificant at its 0.9 quantile. For a given soybean meal quantile, the price movements across its quantile τ_O have a similar M shaped pattern, having two peaks at $\tau_O = 0.2$ and 0.6. The VECQ model estimates of $\lambda_O^+(\mathbf{v})$ at $\tau_O = 0.4$ are the closest to the VEC model estimate of λ_O^+ for any fixed τ_M. Moreover, the cumulative price responses are very close to each other at the low, median, and high quantiles of soybean meal. This indicates that soybean meal returns do not affect the response of soybean oil to increasing input costs. In the case of decreasing soybean prices, there is a downward trend as τ_O increases from 0.1 to 0.9 and the largest responses occur at $\tau_O = 0.1$ regardless of the soybean meal quantile. Although the sign of the cumulative oil response is mixed when τ_M is 0.1 or 0.5, the statistically significant estimates, except for $\tau_O = 0.9$ and $\tau_M = 0.1$, are all positive and the majority are above the VEC model estimate of λ_O^-. When the quantiles of soybean oil and meal are at the extreme low and high, respectively, the cumulative oil price response is 1.49%, well above the VEC model estimate of 0.45%.

Figure 3 plots the difference in cumulative responses of both soybean end products to positive and negative changes in the soybean log price. When this difference is statistically different from zero, we can reject the null hypothesis of price symmetry and infer the existence of price asymmetry. We again plot coefficient estimates that are statistically significant at the 10% level or lower with a filled marker symbol and insignificant estimates with an open marker. For comparison, we show the VEC model estimates by a horizontal line even though they are not statistically different from zero (i.e., there is no price asymmetry). In Figure 3(a), the meal response to increasing soybean price is larger than the response to decreasing input price when the meal log price change itself is at a high quantile of its distribution ($\tau_M = 0.8$ and 0.9) but the oil price change is at the extremely low quantile. Similarly, in Figure 3(b), the soybean oil response exhibits the rockets and feathers pattern when it is above the median of its price change distribution and the meal return is at the lowest quantile. As seen in the figure, the VECQ model reveals an otherwise-hidden confirmation of the rockets and feathers pattern in both output markets.

In summary, we find evidence of price asymmetry when the two end products are at the opposite extremes of their price change distributions. The largest asymmetry in soybean meal and oil prices is 1.06 and 1.07 percentage points, respectively. Furthermore, the signs of price asymmetries found are all positive, indicating that the end products respond more fully to a positive shock in the input price.

Conclusions

This study contributes to the empirical literature of price asymmetry by testing for the first time the occurrence of rockets and feathers pattern in a joint production process and allowing output price responses to vary with the prices of other end products. Our multivariate quantile regression framework not only helps us to search for asymmetry over the entire distribution rather than just at the conditional mean but also allows us to condition the price response of one output on the market conditions of the other output. We show that price responses in any of the soybean end products are not only related to their own return levels but also to the other end product's return. This finding supports the concern of von Cramon-Taubadel and Goodwin (2021) about the price transmission in the case of joint production stating "… the estimation equations may be misspecified because price transmission from an agricultural raw product to one of its outputs will likely depend on prices for the other outputs."

Our results further imply that the occurrence of price asymmetries is related to different market conditions. The locality of quantiles reflects the characteristic of data clustering within a specific part of the distribution, which reflects the market conditions. For example, high returns, located in the upper tail of a distribution, might encourage producers to expand their production

in the future, while low returns clustered in the lower tail might indicate excess supply signaling a reduction in future production. Therefore, an estimation method based on conditional quantiles uncovers the heterogeneity in output responses to input price changes at different regions of their distributions and captures the magnitude of price asymmetries associated with a specific market condition. Our findings confirm the rockets and feathers pattern in the soybean complex when the market conditions of the two end products are contrary to each other. Specifically, a positive price asymmetry (i.e., larger response to input price increases) in any end product occurs when its own market is bullish but the other product's market is bearish. This finding indicates that producers are more likely to pass extra production costs onto consumers when one of the end products is facing a high demand (indicating optimistic market sentiment for the future production and higher prices) and the other end product has a lower price point resulting from either low demand or excess supply (indicating pessimistic market sentiment).

Our multivariate quantile approach can supplement the analysis of factors affecting the magnitude of price asymmetry. A prevalent method is to regress the degree of asymmetry on a list of variables proxying the possible causes (e.g., Peltzman 2000; Loy, Weiss, and Glauben 2016). Most previous empirical studies investigate potential causes based on the behavior of input prices, consumer search costs, and the market structure but ignore the heterogeneity in output price responses, which can be incorporated with our method.

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Appendix A: Weak Exogeneity Test across Multivariate Quantiles

Based on the exogeneity definition of Engle, Hendry, and Richard (1983), weak exogeneity tests of potentially endogenous variables are generally performed in partial models of a cointegrated system (Ericsson 1992; Boswijk 1995; Johansen 1992; Johansen and Juselius 1992; Urbain 1993; Boswijk and Urbain 1997). An advantage of either error correction or autoregressive model is that one can form a partial system as a conditional model, in which equations with variables of interest can be regressed on weakly exogenous variables. The partial model is efficient as long as it contains as much information as the full system about the short- and long-run parameters (Johansen 1992).

Being able to treat soybean prices as weakly exogenous in the analysis of soybean meal and oil equations becomes much more important in the multivariate quantile framework due to computational challenges. Our model is a system of three conditional directional quantile functions, and each conditional quantile is estimated with an arbitrary quantile index $\tau \in (0,1)$. Since we select nine quantile indices of each commodity's price distribution, the multivariate quantile $\boldsymbol{\tau}^* = (\tau_M, \tau_O, \tau_S)'$ provides 729 combinations of quantile indices to be estimated in the VECQ model. Treating soybean prices as weakly exogenous reduces the dimension of the multivariate quantile $\boldsymbol{\tau}^*$ from three to two, largely reducing the computational complication (2-dimensional multivariate quantile only has 81 combinations of quantile indices).

To test weak exogeneity of soybean prices across multivariate quantiles, we follow Urbain (1993)'s method introduced in the preliminary analysis to decompose the trivariate VEC model into a structural VEC model for soybean end products and a marginal reduced-form model for soybeans. Tests of weak exogeneity are carried out by estimating the marginal model for soybean prices based on quantile regression, where the coefficients are functions of multivariate quantile $\boldsymbol{\tau}^*$. Then, the weak exogeneity of $p_{S,t}$ can be tested by the joint null hypothesis:

(A1)
$$H_0: \gamma_S(\boldsymbol{\tau}^*) = 0, \boldsymbol{\theta}(\boldsymbol{\tau}^*) = \mathbf{0}.$$

Figure A.1 presents the histogram of the *p*-values, associated with 729 *F*-statistics for the joint hypothesis tests in equation (A.1), along with a vertical line at the *p*-value of 0.05. All *p*-values are greater than even 0.1, showing that both estimated residuals ($\hat{\mathfrak{v}}_t$) and the error correction ($\widehat{EC}_{t-1}$) term are jointly no different than zero in the marginal model. This indicates that weak exogeneity assumption of soybean prices is satisfied across selected multivariate quantiles.
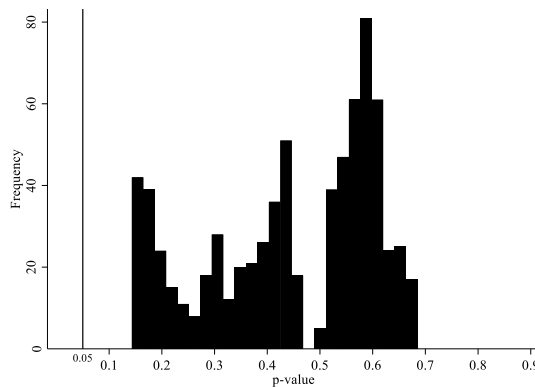
Figure A.1. Weak Exogeneity Tests for Soybean Log Prices across Multivariate Quantiles
Notes: Tests of weak exogeneity of soybean log prices are carried out by estimating the marginal reduced-form model for soybeans based on a quantile regression. The histogram of the *p*-values for 729 null hypotheses given in equation (A.1) are plotted. The vertical line indicates the *p*-value of 0.05.

Appendix B. Adjustment Speed Parameter Estimates of Soybean End Products

Table B.1. Adjustment Speed of Soybean Meal towards the Long-Run Equilibrium

		τ_M								
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
τ_O	0.1	-0.09 **	-0.08 *	-0.08	-0.04	-0.01	0.00	0.00	0.03	-0.02
		(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)
	0.2	-0.11 ***	-0.10 ***	-0.10 **	-0.06	-0.02	-0.02	-0.02	0.01	-0.03
		(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)
	0.3	-0.11 ***	-0.10 ***	-0.10 **	-0.07	-0.03	-0.02	-0.02	0.01	-0.04
		(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)
	0.4	-0.13 ***	-0.12 ***	-0.13 ***	-0.09 **	-0.05	-0.04	-0.04	-0.01	-0.06
		(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)
	0.5	-0.14 ***	-0.13 ***	-0.13 ***	-0.09 **	-0.06 *	-0.05	-0.05	-0.02	-0.06
		(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)
	0.6	-0.14 ***	-0.13 ***	-0.14 ***	-0.10 **	-0.07 *	-0.06	-0.06	-0.03	-0.07
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
	0.7	-0.13 ***	-0.12 ***	-0.13 ***	-0.09 **	-0.06	-0.05	-0.05	-0.02	-0.06
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
	0.8	-0.11 **	-0.10 **	-0.10 **	-0.07	-0.03	-0.02	-0.03	0.00	-0.04
		(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)
	0.9	-0.07	-0.06	-0.06	-0.03	0.01	0.01	0.01	0.04	0.00
		(0.06)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)

Notes: τ_i represents the quantile index of each commodity, where the subscript $i=M$, O represents soybean meal and soybean oil, respectively. The results are rounded to two decimals. Hypothesis testing is based on bootstrapped standard errors given in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. For a comparison, the standard VEC result is -0.10 with a standard error of 0.02, statistically significant at the 1% level.

Table B.2. Adjustment Speed of Soybean Oil towards the Long-Run Equilibrium

		0.1		0.2		0.3		0.4	0.5	0.6	0.7	0.8	0.9	
									τ_O					
	0.1	-0.06		-0.03		-0.02		0.02	0.02	0.04	0.02	-0.02	-0.10	
		(0.07)		(0.04)		(0.04)		(0.04)	(0.05)	(0.05)	(0.05)	(0.08)	(0.09)	
	0.2	-0.07		-0.04		-0.03		0.01	0.02	0.03	0.01	-0.03	-0.11	
		(0.07)		(0.04)		(0.04)		(0.04)	(0.04)	(0.05)	(0.05)	(0.08)	(0.08)	
	0.3	-0.07		-0.04		-0.03		0.01	0.02	0.03	0.01	-0.03	-0.11	
		(0.07)		(0.05)		(0.04)		(0.04)	(0.04)	(0.05)	(0.05)	(0.07)	(0.09)	
	0.4	-0.10		-0.06		-0.06		-0.01	0.00	0.01	-0.01	-0.05	-0.13	
		(0.07)		(0.05)		(0.04)		(0.04)	(0.04)	(0.05)	(0.05)	(0.07)	(0.09)	
τ_M	0.5	-0.12	*	-0.09	*	-0.08	**	-0.04	-0.03	-0.01	-0.03	-0.08	-0.15	*
		(0.07)		(0.05)		(0.04)		(0.04)	(0.04)	(0.04)	(0.04)	(0.07)	(0.08)	
	0.6	-0.13	*	-0.10	**	-0.08	**	-0.05	-0.03	-0.02	-0.04	-0.08	-0.15	*
		(0.07)		(0.05)		(0.04)		(0.04)	(0.04)	(0.04)	(0.04)	(0.07)	(0.08)	
	0.7	-0.13	*	-0.10	*	-0.09	**	-0.05	-0.03	-0.02	-0.04	-0.08	-0.15	*
		(0.07)		(0.05)		(0.04)		(0.04)	(0.04)	(0.05)	(0.04)	(0.06)	(0.08)	
	0.8	-0.15	*	-0.12	**	-0.11	**	-0.07	-0.05	-0.04	-0.06	-0.10	-0.17	**
		(0.08)		(0.06)		(0.05)		(0.05)	(0.05)	(0.05)	(0.05)	(0.07)	(0.08)	
	0.9	-0.12		-0.09		-0.08		-0.04	-0.02	-0.01	-0.03	-0.07	-0.14	*
		(0.08)		(0.06)		(0.05)		(0.05)	(0.05)	(0.05)	(0.05)	(0.07)	(0.08)	

Notes: τ_i represents the quantile index of each commodity, where the subscript $i=M$, O represents soybean meal and soybean oil, respectively. The results are rounded to two decimals. Hypothesis testing is based on bootstrapped standard errors given in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. For a comparison, the standard VEC result is -0.01 with a standard error of 0.03, statistically insignificant at the conventional levels.

Appendix C: Cumulative Price Responses to Soybean Price Changes

Table C.1. Cumulative Price Response of Soybean Meal to Soybean Price Changes

τ_O		τ_M 0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.1	+	**1.28**	**1.29**	**1.09**	**1.05**	**1.26**	**1.19**	**1.35**	**1.50**	**1.21**
	−	**1.40**	**1.00**	**0.90**	**1.02**	**0.94**	**0.86**	**0.87**	**0.63**	0.15
		[0.67]	[0.25]	[0.46]	[0.91]	[0.19]	[0.18]	[0.15]	[0.03] **	[0.02] **
0.2	+	**1.22**	**1.23**	**1.03**	0.99	**1.20**	**1.14**	**1.30**	**1.46**	**1.16**
	−	**1.44**	**1.04**	**0.94**	**1.06**	**0.98**	**0.89**	**0.90**	**0.66**	0.17
		[0.43]	[0.40]	[0.70]	[0.75]	[0.31]	[0.28]	[0.22]	[0.04] **	[0.02] **
0.3	+	**1.28**	**1.30**	**1.10**	**1.06**	**1.27**	**1.20**	**1.36**	**1.51**	**1.22**
	−	**1.51**	**1.12**	**1.02**	**1.14**	**1.07**	**0.97**	**0.98**	**0.74**	0.27
		[0.42]	[0.46]	[0.74]	[0.71]	[0.32]	[0.29]	[0.22]	[0.04] **	[0.02] **
0.4	+	**1.36**	**1.37**	**1.18**	**1.14**	**1.35**	**1.28**	**1.43**	**1.58**	**1.30**
	−	**1.67**	**1.27**	**1.19**	**1.31**	**1.24**	**1.12**	**1.13**	**0.88**	0.42
		[0.27]	[0.69]	[0.96]	[0.44]	[0.56]	[0.48]	[0.32]	[0.05] **	[0.03] **
0.5	+	**1.30**	**1.31**	**1.12**	**1.09**	**1.29**	**1.22**	**1.37**	**1.52**	**1.24**
	−	**1.74**	**1.36**	**1.28**	**1.39**	**1.33**	**1.21**	**1.21**	**0.97**	**0.53**
		[0.12]	[0.85]	[0.48]	[0.16]	[0.83]	[0.96]	[0.60]	[0.12]	[0.07] *
0.6	+	**1.20**	**1.21**	**1.02**	0.98	**1.18**	**1.12**	**1.27**	**1.42**	**1.14**
	−	**1.72**	**1.34**	**1.26**	**1.38**	**1.31**	**1.20**	**1.20**	**0.96**	**0.53**
		[0.07] *	[0.58]	[0.26]	[0.08] *	[0.48]	[0.73]	[0.81]	[0.19]	[0.10] *
0.7	+	**1.25**	**1.26**	**1.07**	**1.04**	**1.23**	**1.18**	**1.33**	**1.47**	**1.20**
	−	**1.73**	**1.35**	**1.27**	**1.39**	**1.32**	**1.21**	**1.21**	**0.97**	**0.54**
		[0.11]	[0.73]	[0.39]	[0.13]	[0.67]	[0.89]	[0.70]	[0.15]	[0.07] *
0.8	+	**1.33**	**1.34**	**1.14**	**1.11**	**1.31**	**1.25**	**1.40**	**1.55**	**1.27**
	−	**1.88**	**1.50**	**1.42**	**1.54**	**1.48**	**1.34**	**1.34**	**1.09**	**0.65**
		[0.08] *	[0.57]	[0.28]	[0.08] *	[0.48]	[0.70]	[0.86]	[0.21]	[0.09] *
0.9	+	**1.43**	**1.44**	**1.26**	**1.22**	**1.42**	**1.34**	**1.49**	**1.63**	**1.36**
	−	**2.07**	**1.71**	**1.64**	**1.75**	**1.71**	**1.55**	**1.55**	**1.30**	**0.89**
		[0.07] *	[0.39]	[0.20]	[0.08] *	[0.32]	[0.49]	[0.87]	[0.40]	[0.21]

Notes: τ_i represents the quantile index of each commodity, where the subscript $i=M$, O represents soybean meal and soybean oil, respectively. For each quantile index, cumulative price responses to soybean price increases are presented in the first row and that to decreases are in the second row. Estimates that are statistically significant at the 10% level or lower are indicated with a bold font. Hypothesis testing of price asymmetry (equality of first and second rows) is based on bootstrapped standard errors and *p*-values are given in brackets. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Shaded cells represent the cases where the equality of cumulative price responses to positive and negative soybean price changes are rejected at the 10% or lower level.

T able C.2. Cumulative Price Response of Soybean Oil to Soybean Price Changes

τ_M		τ_O 0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.1	+	**0.69**	**0.79**	**0.67**	**0.53**	**0.64**	**0.83**	**0.73**	**0.59**	0.40
	−	0.61	**0.52**	0.40	0.10	-0.03	0.01	-0.01	-0.30	**-0.66**
		[0.83]	[0.40]	[0.35]	[0.12]	[0.02] **	[0.00] ***	[0.02] **	[0.02] **	[0.02] **
0.2	+	**0.68**	**0.78**	**0.66**	**0.52**	**0.64**	**0.83**	**0.72**	**0.58**	0.40
	−	**0.89**	**0.82**	**0.67**	0.37	0.22	0.24	0.22	-0.04	-0.44
		[0.53]	[0.89]	[0.98]	[0.58]	[0.11]	[0.03] **	[0.09] *	[0.08] *	[0.06] *
0.3	+	**0.82**	**0.93**	**0.80**	**0.66**	**0.76**	**0.95**	**0.85**	**0.71**	0.51
	−	**0.96**	**0.89**	**0.74**	**0.43**	0.27	0.29	0.28	0.01	-0.40
		[0.70]	[0.89]	[0.80]	[0.37]	[0.05] **	[0.01] ***	[0.04] **	[0.04] **	[0.04] **
0.4	+	**0.85**	**0.96**	**0.83**	**0.68**	**0.78**	**0.97**	**0.87**	**0.74**	0.53
	−	**0.87**	**0.80**	**0.65**	0.35	0.19	0.22	0.20	-0.07	-0.46
		[0.94]	[0.59]	[0.49]	[0.18]	[0.02] **	[0.00] ***	[0.02] **	[0.02] **	[0.03] **
0.5	+	**0.70**	**0.80**	**0.68**	**0.53**	**0.65**	**0.85**	**0.74**	**0.60**	0.41
	−	**0.93**	**0.86**	**0.71**	**0.40**	0.24	0.26	0.24	-0.03	-0.43
		[0.51]	[0.85]	[0.93]	[0.58]	[0.09]	[0.01]	[0.06]	[0.06]	[0.06]*
0.6	+	**0.74**	**0.85**	**0.73**	**0.59**	**0.69**	**0.88**	**0.78**	**0.65**	0.45
	−	**0.99**	**0.92**	**0.77**	**0.48**	0.31	0.34	0.32	0.06	-0.34
		[0.50]	[0.80]	[0.87]	[0.66]	[0.13]	[0.03] **	[0.08] *	[0.08]	[0.07] *
0.7	+	**0.63**	**0.73**	**0.62**	**0.48**	**0.60**	**0.78**	**0.68**	**0.54**	0.36
	−	**0.98**	**0.92**	**0.77**	**0.48**	0.31	0.33	0.32	0.06	-0.34
		[0.36]	[0.57]	[0.61]	[0.99]	[0.31]	[0.10] *	[0.20]	[0.17]	[0.12]
0.8	+	0.52	**0.62**	**0.51**	0.37	**0.50**	**0.69**	**0.59**	0.44	0.28
	−	**1.15**	**1.10**	**0.93**	0.65	**0.47**	**0.49**	**0.47**	0.23	-0.18
		[0.12]	[0.19]	[0.19]	[0.38]	[0.93]	[0.49]	[0.69]	[0.56]	[0.30]
0.9	+	**0.73**	**0.83**	**0.71**	**0.57**	**0.68**	**0.87**	**0.77**	**0.63**	0.44
	−	**1.49**	**1.45**	**1.26**	**0.97**	**0.76**	**0.76**	**0.75**	**0.53**	0.07
		[0.09]*	[0.13]	[0.12]	[0.25]	[0.82]	[0.74]	[0.96]	[0.79]	[0.41]

Notes: τ_i represents the quantile index of each commodity, where the subscript $i=M, O$ represents soybean meal and soybean oil, respectively. For each quantile index, cumulative price responses to soybean price increases are presented in the first row and that to decreases are in the second row. Estimates that are statistically significant at the 10% level or lower are indicated with a bold font. Hypothesis testing of price asymmetry (equality of first and second rows) is based on bootstrapped standard errors and *p*-values are given in brackets. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Shaded cells represent the cases where the equality of cumulative price responses to positive and negative soybean price changes are rejected at the 10% or lower level.