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A Multivariate Quantile Analysis of Price Transmission in the Soybean Complex

by

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Asymmetric price transmission has been an important question for understanding the price relationship among input and output markets in a supply chain. This study investigates asymmetric price transmission in the U.S. soybean complex by using a vector autoregressive quantile model. We use daily returns of the soybean, soybean meal, and soybean oil futures contracts traded at the Chicago Board of Trade (CBOT). To better illustrate dynamics of the own- and cross-market effects, we consider both lower and upper tails and the median of price distributions. Our results indicate existence of asymmetric price transmission varying by the quantile. In addition, quantile impulse response analysis shows that soybean returns at a low level are more severely affected by the shocks from the soybean meal market, while those at a high level are more affected by shocks generating from the soybean oil market.

Key words: asymmetric price transmission, soybean complex, vector autoregressive quantile models, quantile impulse responses

Introduction

Economic theory suggests no tendency for asymmetric price response to changes in the cost; however, it is a common view that consumers respond faster to price increases as opposed to price decreases. This conflict raised the interest of economists to explore the source of price stickiness (Blinder 1982; Fershtman and Kamien 1987) and measure the degree of asymmetric price response in commodity markets (Peltzman 2000; Bils and Klenow 2004). The existence and prevalence of asymmetric price transmission, especially in agricultural commodity markets, has been investigated over decades (Meyer and von Cramon-Taubadel 2004). This is because not all agricultural commodities are imperishable. Asymmetric price transmission is more likely to occur in markets where commodities are storable (Blinder 1982). The literature on price asymmetry is generally based on either short-run or long-run analysis (Frey and Manera 2007). Short-run asymmetry is captured by output price movements in response to positive or negative changes in input prices, while long-run asymmetry is identified by reaction times, length of price fluctuations, and speed of price adjustment toward an equilibrium level. Most popular econometric models for studying price asymmetries include distributed lags, partial adjustment, error correction, regime switching, and vector autoregressive models. These models are based either on OLS or method of moments, which capture global features of a distribution and are strongly influenced by the extremes.

Quantiles are local and nearly impervious to small perturbations of the distributional mass (Koenker 2017). Therefore, quantile estimators are robust to the extremes, which is an advantage over OLS and method of moments. Moreover, quantile regression provides a comprehensive picture of a regression analysis by investigating the relationship between variables over the entire conditional distribution. The application of quantile regression is a new approach for investigating asymmetric price response of outputs to the changes in inventory or input prices (Chavas and Li 2020; Chavas and Pan 2020). Moreover, the concept of quantile regression is extended to vector autoregressive models (VAR) for analyses of asymmetric effects of financial conditions such as excess bond premium on real economy represented by the U.S. industrial production (Falconio and Manganelli 2019) and asymmetric propagation of shocks caused by monetary policy adopted to address output gap and inflation (Montes-Rojas 2019). The application of quantile regression in VAR models sheds light on the pattern of price transmission between input and output markets since it provides a more focused source of asymmetry at different locations of price distributions.

The goal of this study is to identify asymmetric price transmission and explore its pattern in the soybean complex by using a vector autoregressive quantile (VARQ) model. Since soybean is the primary input for soybean meal and oil, Rausser and Carter (1983) study price comovements among the soybean complex futures contracts traded in the U.S. exchange. . Furthermore, a thorough understanding of price correlations in the soybean complex is useful for various topics, such as multi-product hedging strategies (Garcia, Roh, and Leuthold 1995; Tejeda and Goodwin 2014), economic value of public information (Karali 2012), arbitrage opportunities in the soybean crush spread (Johnson et al. 1991; Mitchell 2010; Marowka et al. 2020), and forecasting performance of futures prices (Huang, Serra, and Garcia 2020). Our paper expands on these previous studies and provides a comprehensive analysis of price relationships within the soybean complex with special emphasis given to heterogeneity in price movements over the entire distribution.

Methodology

Quantile regression is an important method introduced by Koenker and Bassett (1978), which expands the least-squares estimation for the conditional mean to the quantile estimation for conditional quantiles over entire distribution of the response. In contrast to moments, which characterizes global features and are consequently influenced by tail behaviors, the conditional quantiles are local and exhibit robustness to extremes (Koenker 2017). In particular, it is frequently found that the distribution of commodity prices or returns is asymmetric and displays excess kurtosis (Fama 1965; Deaton and Laroque 1992; Fernandez-Petez et al. 2018). The application of univariate quantile regression in the study of times series provides more flexible modeling options for risk management and asymmetric price dynamics. These studies can be basically grouped into three categories[1]: (1) quantile autoregressive model (QAR), (2) conditional autoregression value at risk by regression quantiles (CAViaR), and (3) quantile estimation for ARCH/GARCH models. Quantile autoregression models study the effects of conditioning variables across different quantiles of the distribution of response (Koenker and Xiao 2006) and are used in study of asymmetric price dynamics in commodity markets (Chavas and Li 2019). CAViaR is a local approach to directly model the movement of value at risk (VaR) at a selected quantile (Engle and Manganelli 2004; Laporta, Merlo, and Petrella 2018). A conditional quantile estimator for return volatility is first studied in linear ARCH model (Koenker and Zhao 1996), then it extends to generalized ARCH (GARCH) models (Xiao and Koenker 2009; Lee and Noh 2013). To solve the non-smooth and non-convex optimization in the quantile estimation for GARCH models, a hybrid quantile estimator for univariate GARCH

[1] The whole literature for the application of quantile regression in times series models is too vast to be reviewed in our paper, but an excellent review on QAR and quantile time series analysis can be found in Xiao (2017).

model is designed for practical feasibility and used in different specifications of GARCH models (Zheng et al. 2018; Wang et al. 2020; Zhu, Li, and Xiao 2020).

However, multivariate quantiles are more complicated than univariate ones. The lack of a natural ordering of a multidimensional Euclidean space leads to a loose definition[2] of multivariate quantile methods when extending the univariate quantile functions to multivariate cases. Serfling (2002) reviews four common approaches[3] among vector-valued extensions of univariate quantile functions and recommends the median-oriented quantile functions as a standard approach for multivariate quantile analysis, especially those functions based on depth functions. The depth functions derive from more geometric considerations and has the advantages of attractive equivariance properties and intuitive contents (Hallin, Paindaveine, and Šiman 2010; Serfling and Zuo 2010). An extensive theoretical literature exists on the geometric quantiles and depth contours for multivariate data (Chaudhuri 1996; Liu, Parelius, and Singh 1999; Wei 2008; Kong and Mizera 2012; Chernozhukov et al. 2017). Directional quantiles shed light on the definition of multivariate quantiles, which indexes quantiles for multi-output regression by directional vectors ranging over an open unit ball (Hallin, Paindaveine, and Šiman 2010; Kong and Mizera 2012). This interpretation not only provides a simple way to regress depth contours on covariates, but also can be adopted to elaborate frameworks for multivariate random variables, such as directional quantile regression (Paindaveine and Šiman 2011) and reduced-form directional quantiles (Montes-Rojas 2017, 2019).

Our paper builds on the study of Montes-Rojas (2017,2019) and studies the price transmission among soybean complex at different quantiles of return distributions by using vector autoregressive quantiles (VARQ) model. The VARQ model simultaneously collect quantile autoregressive models for a fixed orthonormal basis, in which projected points represents a directional quantile of the corresponding response variable. According to Hallin, Paindaveine, and Šiman (2010), the quantile vector $\boldsymbol{\tau} = (\tau_1, \dots \tau_m)'$ of a random vector $\mathbf{Y} = (y_1, \dots y_m)'$ naturally decomposes into $\boldsymbol{\tau}$:=$\tau\boldsymbol{d}$, where quantile index $\tau = \|\boldsymbol{\tau}\| \in (0,1)$ associated with a m ×1 directional vector $\boldsymbol{d}$, indicating reference direction for single-output regression quantiles defined by Koenker and Bassett (1978). $\boldsymbol{\Gamma_d}$ is defined as an arbitrary m×(m-1) matrix of directional vectors, which represents other directional vectors orthogonal to $\boldsymbol{d}$ and ($\boldsymbol{d}$, $\boldsymbol{\Gamma_d}$) constitutes an orthonormal basis of $\mathbb{R}^m$. Therefore, the $\boldsymbol{\tau}$-quantile of $\mathbf{Y}$ is any element of the collection of the τ-quantile hyperplane $\pi_{\boldsymbol{\tau}}$ obtained when regressing $\boldsymbol{d}'\mathbf{Y}$ on $\boldsymbol{\Gamma_d}'\mathbf{Y}$ and a constant (Hallin, Paidaveine, Šiman 2010). Montes-Rojas (2019) extends this definition to vector autoregressive framework. For a fixed orthonormal basis, the VARQ model is based on a system of single-output quantile autoregressions. The vector directional quantile is defined in our paper as follows:

[2] There is a substantial lecture, for example, including the multivariate extension of CAViaR models (White, Kim, and Manganelli 2015; Chaleishvili and Manganelli 2019; Falconio and Manganelli 2020), an optimal transport maps the vector quantile of responses between the probability of multivariate explanatory variables and a unit ball of the same dimension (Carlier, Chernozhukov, and Galichon 2016, 2017), and a transformation retransformation approach (Chakraborty 2003). Besides the vector-valued extensions, Bayesian estimation is applied to find the joint quantiles of multivariate distribution (Cai 2010) and copula-based quantile models decompose any multivariate distribution into marginal distributions which are linked by a copula (Bernard and Czado 2015; Chavas and Pan 2020).

[3] The other three approaches are based on norm minimization, inversions of mappings, and data-based gradients.

(1) $\{\boldsymbol{\gamma}(\boldsymbol{\tau}, \boldsymbol{d}, \boldsymbol{\Gamma_d})', \ \boldsymbol{\beta}(\boldsymbol{\tau}, \boldsymbol{d}, \boldsymbol{\Gamma_d})', \alpha(\tau, d)\} \equiv \text{argmin E}\{\rho_\tau(\boldsymbol{d}'\mathbf{R}_t - \boldsymbol{\gamma}'\boldsymbol{\Gamma_d}'\mathbf{R_t} - \boldsymbol{\beta}'\mathbf{R_{t-1}} - \alpha)\},$

where the $\mathbf{R}_t$ and $\mathbf{R_{t-1}}$ as the vector of close-to-close returns in soybean complex at time *t* and *t-1*, respectively. We denote $\boldsymbol{\tau} = (\tau_s, \tau_m, \tau_o)'$ as quantile index of $\mathbb{R}^3$, which is a multivariate element of an open unit ball. $\boldsymbol{d}$ is a 3×1 directional vector and $\boldsymbol{\Gamma_d}$ is a 3×2 matrix for directional vectors of other two commodities. $\rho_\tau(\varepsilon) = \varepsilon(\tau - I(\varepsilon < 0))$ is the loss function defining the same as univariate quantile functions. More specifically, the conditional quantile function of VARQ model, $Q_{\mathbf{R_t}}(\boldsymbol{\tau}|\boldsymbol{\mathcal{F}_{t-1}}) = (q_s(\boldsymbol{\tau}|\mathcal{F}_{t-1}), q_m(\boldsymbol{\tau}|\mathcal{F}_{t-1}), q_o(\boldsymbol{\tau}|\mathcal{F}_{t-1}))'$, can be obtained from a system of three equations,

$$q_s(\boldsymbol{\tau}|\boldsymbol{\mathcal{F}_{t-1}}) = \boldsymbol{\gamma_{-s}}(\tau_s)'\boldsymbol{q_{-s}}(\boldsymbol{\tau}|\boldsymbol{\mathcal{F}_{t-1}}) + \boldsymbol{\beta_s}(\tau_s)'\mathbf{R_{t-1}} + \alpha_s(\tau_s)$$

$$q_m(\boldsymbol{\tau}|\boldsymbol{\mathcal{F}_{t-1}}) = \boldsymbol{\gamma_{-m}}(\tau_m)'\boldsymbol{q_{-m}}(\boldsymbol{\tau}|\boldsymbol{\mathcal{F}_{t-1}}) + \boldsymbol{\beta_m}(\tau_m)'\mathbf{R_{t-1}} + \alpha_m(\tau_m)$$

(2) $$q_o(\boldsymbol{\tau}|\boldsymbol{\mathcal{F}_{t-1}}) = \boldsymbol{\gamma_{-o}}(\tau_o)'\boldsymbol{q_{-o}}(\boldsymbol{\tau}|\boldsymbol{\mathcal{F}_{t-1}}) + \boldsymbol{\beta_o}(\tau_o)'\mathbf{R_{t-1}} + \alpha_o(\tau_o),$$

where $\boldsymbol{\mathcal{F}_{t-1}}$ is the information set. $\boldsymbol{q_{-i}}(\boldsymbol{\tau}|\boldsymbol{\mathcal{F}_{t-1}})$ corresponds to the $\boldsymbol{\tau}$ −quantile of $\mathbf{R_t}$ that exclude the *ith* variable. $\boldsymbol{\gamma_{-i}}(\tau_i)$ is a 2×1 vector excluding the *ith* variable, $\boldsymbol{\beta_i}(\tau_i)$ is a 3×1 vector and $\alpha_i(\tau_i)$ is a scalar, where *i* = *m* (soybean meal), *o* (soybean oil), and *s* (soybean).
Rewrite $\boldsymbol{\gamma}(\boldsymbol{\tau}) = \begin{bmatrix} 0 & \gamma_m(\tau_s) & \gamma_o(\tau_s) \\ \gamma_s(\tau_m) & 0 & \gamma_o(\tau_m) \\ \gamma_s(\tau_o) & \gamma_m(\tau_o) & 0 \end{bmatrix}$ is a 3× 3 matrix, $\boldsymbol{\beta}(\boldsymbol{\tau}) = \left(\boldsymbol{\beta}_s(\tau_s), \boldsymbol{\beta}_m(\tau_m), \boldsymbol{\beta}_o(\tau_o)\right)'$ is a 3×3 matrix and $\boldsymbol{\alpha}(\boldsymbol{\tau}) = \left(\alpha_s(\tau_s), \alpha_m(\tau_m), \alpha_o(\tau_o)\right)'$ is a 3×1 vector. Therefore, VARQ model is rewritten as,

(3) $$\boldsymbol{Q}_{\mathbf{R}_t}(\boldsymbol{\tau}|\boldsymbol{\mathcal{F}}_{t-1}) = \boldsymbol{\theta}_0(\boldsymbol{\tau}) + \boldsymbol{\theta}_1(\boldsymbol{\tau})\mathbf{R}_{t-1},$$

where $\boldsymbol{\theta}_0(\boldsymbol{\tau})$= $(\mathbf{I}_3 - \boldsymbol{\gamma}(\boldsymbol{\tau}))^{-\mathbf{1}}\,\boldsymbol{\alpha}(\boldsymbol{\tau})$, $\boldsymbol{\theta}_1(\boldsymbol{\tau})$=$(\mathbf{I_3} - \boldsymbol{\gamma}(\boldsymbol{\tau}))^{-\mathbf{1}}\,\boldsymbol{\beta}(\boldsymbol{\tau})$, and $\mathbf{I}_3$ is a 3×3 identity matrix.

The main effect of interest, $\boldsymbol{\theta}_1(\boldsymbol{\tau})$, is own and cross effects of lagged returns on current returns, which depends on the multivariate quantile index $\boldsymbol{\tau}$. Furthermore, we use quantile impulse response functions (QIRF) to investigate the effects of shocks from a given market on the entire system for soybean complex at different quantiles.

Data Construction

Soybean is the primary input for soybean processors to produce soybean oil and meal, and therefore fluctuations in the price of soybean should result in corresponding fluctuations in soybean meal and oil prices. Soybean processors are simultaneously faced with the price risks from both input and output markets. These price risks can be hedged by a long futures position for soybean and a short futures position for soybean meal and oil before any cash market transaction occurs (Garcia, Roh, and Leuthold 1995). This hedging strategy links futures markets of soybean, soybean meal and oil (soybean complex) in a crushing process.

We use futures contracts in soybean complex traded at the CBOT. CBOT, the world's largest grains futures market, provides the most active and liquid futures contracts for U.S. soybean complex. The soybean contracts have seven delivery months with a standard contract size of 5,000 bushels and the price is quoted in U.S. cents per bushel. On the other hand, both soybean meal and oil contracts have eight delivery months but with different contract size. Soybean meal has a contract size of 100 short tons and the prices are quoted in U.S. dollars per short ton, while Soybean oil has a contract size of 60,000 pounds and prices are quoted in U.S. cents per pound. The specifications for these three futures contracts are shown in Table A.1 in appendix.

Our futures price data are obtained from Bloomberg covering the period from January 2, 1992 to June 30, 2020. We exclude the days with national holidays in either country to eliminate mismatched prices and convert all price quotations into U.S. dollar per bushel of soybean. Table 1 lists the specific futures contracts used in each calendar month to construct futures price series. We create nearby CBOT futures price series by rolling over the contracts at the end of the month prior to maturity (to avoid the delivery period) while excluding the contracts that are not actively traded (August and September contracts). To allow time for the soybean crushing process (Karali 2012), we use CBOT soybean meal and oil contracts that expire two to four months later than the soybean contract while excluding the contracts that are illiquid (August and October contracts). All price series are nonstationary, not normally distributed and have autocorrelation with 5 lags and 45 lags.[4]

Let $P_{i,t}$ denote the closing price of commodity *i* on day *t*, where *i* = *m* (soybean meal), *o* (soybean oil), and *s* (soybean). Daily returns on these selected futures prices are measured as $R_{i,t} = 100 \times (ln\ P_{i,t} - ln\ P_{i,t-1})$. Table 2 presents summary statistics for these returns. The average return for CBOT soybean meal, soybean oil, and soybean are 0.03, -0.01, and 0.02, respectively. The soybean meal has the largest standard deviation of 1.49, while the standard deviation of the soybean oil is the lowest, 1.37. The distributions of all three returns are asymmetric. The distribution of either soybean or soybean meal is negatively skewed, indicating the left tail is longer and most of the return distribution is at the right, while the returns distribution of soybean oil is positively skewed. In addition, we reject the existence of normality in all returns, indicating they are not normally distributed. Based on the augmented Dickey-Fuller (ADF) tests, all returns reject the existence of a unit root, implying they are stationary. Moreover, we reject no autocorrelation with five lags for soybean meal and soybean at 10% significant level while we fail to reject it for soybean oil. But all three returns are rejected the null hypothesis of no autocorrelation when the lags are forty.

[4] Table A.2 in the appendix shows summary statistics of the resulting futures price series. The average price for CBOT soybean meal, soybean oil, and soybean are \$5.62/bushel, \$3.37/bushel, and \$8.35/bushel, respectively. The U.S. soybean futures price has the largest standard deviation of 2.98, while the standard deviation of the soybean oil price is the lowest, 1.24. Based on the augmented Dickey-Fuller (ADF) tests, all price series fail to reject the existence of a unit root. In addition, we reject the existence of normality in all price series, indicating they are not normally distributed. Moreover, we reject no autocorrelation in all futures prices.

Results

The VARQ model is a possible way to condense directional quantile information from each commodity market in soybean complex. It helps to investigate the dependencies among soybean and its products at different quantiles of price distributions. The coefficients for soybean meal, soybean oil, and soybean are reported in figures 1, 2, and 3, respectively. Each dot corresponds to an estimate affected by multivariate quantile $\boldsymbol{\tau} = (\tau_s, \tau_m, \tau_o)'$, while the straight red line gives the OLS estimate of the corresponding vector autoregressive (VAR) model. The VARQ estimates are not only affected by the quantiles of its own distribution, but also are affected by the quantiles of the distributions of other commodities in the system. Since quantile index can be a random value within 0 and 1, there exists infinite choices for multivariate quantile $\boldsymbol{\tau}$. For brevity, we consider 19 quantile indexes of the distribution of a given commodity from 0.05 to 0.95, while we select three specific quantile indexes (τ =0.05, 0.5, and 0.95) of the distribution of other two commodities.

Own and cross effects at different multivariate quantiles

The results in figure 1 show the heterogeneity in the responses of soybean meal returns to the changes in lagged variables at different multivariate quantiles. The VARQ estimates are very closed to OLS estimates when quantiles of all three commodities are at median, while the difference between these two estimates become larger at both tails. When keeping τ_s and τ_o constant, the coefficients of lagged soybean meal and oil returns both have a downward trend while that of lagged soybean has an upward trend as τ_m increases. Since soybean is the primary input for producing soybean meal, we are interested in investigating the cross effects from lagged soybean return on current soybean meal returns. The coefficients of lagged soybean returns are negative at lower quantiles while they are positive at higher quantiles, indicating an increase in lagged soybean returns leads to a decrease in low soybean meal returns but increases the returns of soybean meal at higher price levels. When fixing the quantile index of soybean meal distribution, we can compare the changes in estimates in response to different quantiles from other commodities, τ_s and τ_o. We find the own and cross effects of lagged variables are independently affected by quantiles of soybean distribution, since all estimates are monotonically increasing (or decreasing) as τ_s increases regardless of the selection for τ_o. More specially, the coefficients for lagged soybean returns are all negative at the low soybean quantile (τ_s =0.05) and almost be positive at the high soybean quantile (τ_s =0.95). It implies that for a given quantile of soybean meal, lower lagged soybean returns lead to a decrease in the current returns of soybean meal while higher returns contribute to an increase.

Another important product for soybean crushing is soybean oil. In figure 2, we present the heterogeneity in responses of soybean oil to the changes in lagged variables over the whole distribution. We can also find that their estimates are very closed to OLS estimates when quantiles of all three commodities are at median. However, there do not exist an upward or downward trend across the quantiles of its own distribution. Moreover, the quantiles of soybean and soybean meal jointly affect the magnitude of the coefficients for lagged variables when soy meal returns are at extremely low quantiles. To investigate the price transmission from soybean market to soybean oil market, we focus on the changes in coefficients for lagged soybean returns. At any given quantile of soybean oil, we find that coefficients for lagged soybean returns are all negative when soybean quantile is extremely low (τ_s =0.05) and soybean meal quantile is low (either τ_m =0.05 or τ_m =0.50), while they are all positive when soybean quantile is extremely high (τ_s =0.95) and soybean meal quantile is high (either τ_m =0.50 or τ_m =0.95). It implies, regardless of its own quantiles, an increase in soybean returns has a negative impact on soybean oil when both soybean and soybean oil returns are at lower quantiles and has a positive impact when the two commodities are at higher quantiles.

The market demand for soybeans is directly determined by the prices of its two major products, therefore we explore the heterogeneous responses of soybean to lagged soybean meal and oil in figure 3. When keeping τ_m and τ_o the same, the coefficients of lagged soybean meal and oil returns both have a downward trend while that of lagged soybean has an upward trend as τ_s increases. For any given τ_s, we find the coefficients for lagged soybean oil are independently affected by the quantile of soybean meal, and they move from positivity to negativity as τ_m increases. However, the coefficients for lagged soybean meal are jointly affected by the quantiles of soybean meal and oil since there are no clear patterns as either τ_m or τ_o increases. In summary, either soybean meal returns or soybean oil returns at a low quantile have a positive impact on the returns of soybean while those at a high quantile have a negative impact.

Quantile impulse response functions

To better understand price dynamics at different quantiles, we perform quantile impulse response analyses, which measure simultaneous movements in soybean complex by way of indexing them by $\boldsymbol{\tau}$ and describe the behavior of a series in response to a shock hitting the series. We evaluate the propagation of exogenous shocks at three selected quantiles: extremely low quantile ($\boldsymbol{\tau}$=0.05), median ($\boldsymbol{\tau}$=0.5), and extremely high quantiles ($\boldsymbol{\tau}$=0.95). Also, we compare quantile impulse response functions (QIRF) with impulse response functions of VAR model. The shock is equivalent to one unit increase in the conditional returns of the market where it first occurs.

Figures 4 through 5 show the simulated responses in the returns of soybean products to shocks generating from soybean market, respectively. Controlling for the quantiles of the other two commodities, soybean and soybean oil, we can observe the potential response of soybean meal returns to a change in its input material when soybean meal returns are at 5%, 50%, and 95% conditional quantile in figure 4, respectively. More specially, when the market condition is depressed ($\tau_s = 0.05$ and $\tau_o = 0.05$), the conditional return of soybean meal is instantly and negatively affected by shocks from soybean market. The magnitude of this impact is more severely for soybean meal returns at 5% quantile but the changes for all selected three quantile indexes are decreasing to zero at 4 days, implying a short-term impact. In contrast, a shock from the input market leads to an instant and positive impact on soybean meal market in a deficient market environment ($\tau_s = 0.95$ and $\tau_o = 0.95$). The changes are more volatile at 50% and 95% conditional quantiles, which are increasing to a peak at 1day, sharply decreasing with a bottom at 2 days, and then slight vacillating to zero at around 5 days. Moreover, when market condition is neutral ($\tau_s = 0.5$ and $\tau_o = 0.5$), the response of 50% soybean meal returns is similar to that of conditional mean (which is estimated by VAR model), which is decreasing to zero at 2 days. In addition, the responses of 5% and 95% have an opposite reaction to the shock in a neutral market, indicating a shock in soybean market spurs an increase in higher returns while suppresses the lower returns.

The simulated responses of soybean oil returns at 5%, 50%, and 95% quantile to the shocks generating from the soybean market are presented in figure 5, respectively. When the market environment is depressed ($\tau_s = 0.05$ and $\tau_m = 0.05$), the changes in soybean oil returns at different quantiles all drop to the bottom at 1 day before they fade away around 4 days. Moreover, 95% of soybean oil returns are more severely affected than those at 50% after the soybean shock enters the soybean oil market, and the change in 95% returns swifts to be positive at 2 days. In contrast, when market condition is optimistic ($\tau_s = 0.95$ and $\tau_m = 0.95$), the change in 95% returns is more volatile and persistent than the those in 5% and 50%. The changes in 5% and 50% returns are closed to zero at 3 days but there is a positive response to the soybean shock for 95% returns. When the quantiles of soybean and soybean meal are both at median, the soybean shock has a negative impact on extremely low quantile but there is almost no impact on 50% and 95% returns. This finding is different to the QIRFs of soybean meal, whose 5% and 95% returns have an opposite reaction to soybean shocks, although the response of 50% quantile of both returns are very closed to that of the conditional mean.

Comparing to figures 4 and 5, figures 6 through 8 show heterogeneity of the soybean responses to the shocks generating from its two major products. We first investigate the shocks from a single commodity market, either soybean meal or oil, in figures 6 and 7, respectively. Also, the soybean returns are simultaneously affected by the shocks from these two markets in figure 8. We can observe a similar pattern for price transmission from soybean products to the soybean market. The difference in these three figures is in the magnitude of the responses. Especially, comparing to a unit shock from either soybean meal or oil, the response of soybean returns at 95% quantile is more severely affected by the shock from soybean oil while those at 5% quantile are more affected by soybean meal shock. It is evident from the existence of asymmetric price transmission from soybean products to soybean market at different quantiles of price distribution.

Conclusion

The vertical price transmission among input and output markets is an important characteristic of a supply chain. Furthermore, the extent of adjustment and speed with which shocks are transmitted among these markets is an important factor reflecting the actions of market participants and evaluating the price risks in the supply chain. Studying the nature, speed, and adjustments to market shocks helps to provide some important implications for marketing margins and trading spreads. Vector autoregressive models is one of the most popular econometric models applied in multiple markets, especially for asymmetric price transmission. The vector autoregressive approach provides a statistical tool to simultaneously estimate lagged effects and their linkages with evolving price shocks. However, the least squares estimation gives a rather incomplete regression picture since it estimates parameters based on expected values, which gives a grand summary for the distribution at its conditional mean (Koenker and Hallock 2001). Our paper contributes to the study of price transmission by using the vector autoregressive quantile model that allows asymmetry at different multivariate quantiles. We further investigate the changes in return spillovers from soybean products to soybean and vice versa under three different market conditions.

Market conditions, such as fundamentals and sentiment, are reflected by the changes in market prices. When commodity returns are at low quantiles, this corresponds to high inventories of these products indicating a possible depression in future production. In contrast, high commodity returns usually indicate a deficient market associated with low inventories. Therefore, the VARQ estimates not only describe the sign and magnitudes of own- and cross-effects of lagged variables, but also imply the changes in price relationships in response to different market conditions. The VARQ coefficients in the soybean complex estimated at the median quantile are similar to those from a VAR model estimated by least squares. Since the demand for soybean is derived by the demand for its major products, one of our main goals is to investigate the effects of soybean meal and oil on the soybean market. Controlling for the quantiles of soybean products, we analyze these cross effects on soybean returns by varying its own quantile. When market condition for soybean products is bullish (i.e. higher prices), soybean returns at lower quantiles are positively correlated with the returns of its products, but those at higher quantiles are negatively correlated. This is not surprising as high returns in soybean products spur the purchase of soybean for crushing when the input price is low. However, it is surprising to find positive correlation between soybean returns and both meal and oil returns regardless of its own quantile when the market condition for soybean products is bearish (i.e. lower prices).

Our findings for return reactions at different quantiles show that the magnitude of responses is much larger at both tails than at the median. Moreover, soybean returns at a low quantile are more severely affected by shocks from the soybean meal market, while those at a high quantile are more affected by shocks generating from the soybean oil market. These findings provide a new view for processors and policy makers to understand asymmetric price transmission among the input and output markets which are linked by a supply chain.

References

Bernard, C., and C. Czado. 2015. "Conditional Quantiles and Tail Dependence." *Journal of Multivariate Analysis* 138:104-126.

Bils, M., and P.J. Klenow. 2004. "Some Evidence on the Importance of Sticky Prices." *Journal of Political Economy* 112(5):947-985.

Blinder, A. S. 1982. "Inventories and Sticky Prices: More on the Microfoundations of Macroeconomics." *The American Economic Review* 72(3):334-348.

Carlier, G., V. Chernozhukov, and A. Galichon. 2016. "Vector Quantile Regression: An Optimal Transport Approach." *Annals of Statistics* 44(3):1165-1192.

Carlier, G., V. Chernozhukov, and A. Galichon. 2017. "Vector Quantile Regression beyond the Specified Case." *Journal of Multivariate Analysis* 161: 96-102.

Chavas, J. P., and J. Li. 2020. "A Quantile Autoregression Analysis of Price Volatility in Agricultural Markets". *Agricultural Economics* 51(2): 273-289.

Chavas, J. P., & Pan, F. 2020. "The Dynamics and Volatility of Prices in a Vertical Sector." *American Journal of Agricultural Economics* 102(1):353-369.

Chernozhukov, V., A. Galichon, M. Hallin, and M. Henry. 2017. "Monge–Kantorovich Depth, Quantiles, Ranks and Signs." *The Annals of Statistics* 45(1):223-256.

Deaton, A., and G. Laroque. 1992. "On the Behaviour of Commodity Prices." *The Review of Economic Studies* 59(1):1-23.

Falconio, A. and S. Manganelli. 2020. "Financial Conditions, Business Cycle Fluctuations and Growth at risk." ECB Working Paper No. 2470, European Central Bank (ECB): Frankfurt a. M. Retrieved by http://dx.doi.org/10.2866/891726

Fama, E. 1965. "The Behavior of Stock-Market Prices." *The Journal of Business* 38(1):34-105. Retrieved from http://www.jstor.org/stable/2350752

Fershtman, C., and M.I. Kamien. 1987. "Dynamic Duopolistic Competition with Sticky Prices." *Econometrica: Journal of the Econometric Society* 55(5): 1151-1164.

Frey, G., and M. Manera. 2007. "Econometric Models of Asymmetric Price Transmission." *Journal of Economic surveys* 21(2):349-415.

Garcia, P., S.H. Irwin, and A. Smith. 2015. "Futures Market Failure?" *American Journal of Agricultural Economics* 97(1):40-64.

Garcia, P., J.S. Roh, and R.M. Leuthold. 1995. "Simultaneously Determined, Time-varying Hedge Ratios in the Soybean Complex." *Applied Economics* 27(12):1127-1134.

Huang, J., T. Serra, and P. Garcia. 2020. "Are Futures Prices Good Price Forecasts? Underestimation of Price Reversion in the Soybean Complex." *European Review of Agricultural Economics* 47(1):178-199.

Johnson, R.L., C.R. Zulauf, S.H. Irwin, and M.E. Gerlow. 1991. "The Soybean Complex Spread: An Examination of Market Efficiency from the Viewpoint of a Production Process." *Journal of Futures Markets* 11(1):25-37.

Karali, B. 2012. “Do USA Announcements Affect Comovements Across Commodity Futures Returns?” *Journal of Agricultural and Resource Economics* 37(1):77-97.

Koenker, R., and G. Bassett Jr. 1978. “Regression Quantiles.” *Econometrica: Journal of the Econometric Society* 46(1):33-50.

Koenker, R., and K.F. Hallock. 2001. “Quantile Regression.” *Journal of Economic Perspectives* 15(4):143-156.

Kong, L., and I. Mizera. 2012. “Quantile Tomography: Using Quantiles with Multivariate Data.” *Statistica Sinica* 1589-1610.

Laporta, A.G., L. Merlo, and L. Petrella. 2018. “Selection of Value at Risk Models for Energy Commodities.” *Energy Economics* 74:628-643.

Liu, R.Y., J.M. Parelius, and K. Singh. 1999. “Multivariate Analysis by Data Depth: Descriptive Statistics, Graphics and Inference.” *The Annals of Statistics* 27(3):783-858.

Marowka, M., G.W. Peters, N. Kantas, and G. Bagnarosa. 2020. “Factor-augmented Bayesian Cointegration Models: A Case-Study on the Soybean Crush Spread.” *Journal of the Royal Statistical Society: Series C (Applied Statistics)* 69(2):483-500.

Meyer, J., and S.Von Cramon-Taubadel. 2004. “Asymmetric Price Transmission: A Survey.” *Journal of Agricultural Economics* 55(3):581-611.

Mitchell, J.B. 2010. “Soybean Futures Crush Spread Arbitrage: Trading Strategies and Market Efficiency.” *Journal of Risk and Financial Management* 3(1):63-96.

Montes-Rojas, G. 2017. “Reduced Form Vector Directional Quantiles.” *Journal of Multivariate Analysis* 158: 20-30.

Montes-Rojas, G. 2019. “Multivariate Quantile Impulse Response Functions.” *Journal of Time Series Analysis* 40(5):739-752.

Paindaveine, D., and M. Šiman. 2011. “On Directional Multiple-Output Quantile Regression.” *Journal of Multivariate Analysis* 102(2):193-212.

Plato, G.E. 2001. “The Soybean Processing Decision: Exercising a Real Option on Processing Margins” (No. 1488-2016-124727).

Peltzman, S. 2000. “Prices Rise Faster than They Fall.” *Journal of Political Economy* 108(3):466-502.

Rausser, G.C., and C. Carter. 1983. “Futures Market Efficiency in Soybean Complex.” *The Review of Economics and Statistics* 65(3):469-478.

Serfling, R. 2002. “Quantile Functions for Multivariate Analysis: Approaches and Applications.” *Statistica Neerlandica* 56(2):214-232.

Xiao Z. 2017. “QAR and Quantile Time Series Analysis.” In R. Koenker, V. Chernozhukov, X. He, and L. Peng, eds. *Handbook of Quantile Regression*. Boca Raton, FL: CRC Press, pp.293-329.

Table 1. CBOT Futures Contracts Used in Constructing Price Series

Calendar Month	Soybean Meal	Soybean Oil	Soybean
$January_t$	May_t	May_t	Mar_t
$February_t$	May_t	May_t	Mar_t
$March_t$	Jul_t	Jul_t	May_t
$April_t$	Jul_t	Jul_t	May_t
May_t	Sep_t	Sep_t	Jul_t
$June_t$	Sep_t	Sep_t	Jul_t
$July_t$	Dec_t	Dec_t	Nov_t
$August_t$	Dec_t	Dec_t	Nov_t
$September_t$	Jan_{t+1}	Jan_{t+1}	Nov_t
$October_t$	Jan_{t+1}	Jan_{t+1}	Nov_t
$November_t$	Mar_{t+1}	Mar_{t+1}	Jan_{t+1}
$December_t$	Mar_{t+1}	Mar_{t+1}	Jan_{t+1}

Notes: CBOT = Chicago Board of Trade. The subcript, t or t+1, refers to the year of the futures contract expiration date relative to the year t of the daily price being calculated.

Table 2. Summary Statistics of CBOT Futures Returns

	Soybean Meal	Soybean Oil	Soybean
Mean	0.025	-0.008	0.015
Std. Dev.	1.493	1.368	1.385
Min	-7.832	-7.138	-7.411
Max	7.641	8.080	6.695
Skewness	-0.008	0.143	-0.149
Kurtosis	5.543	5.186	5.562
Observations	7109	7109	7109
ADF test	-35.535 ***	-34.262 ***	-35.434 ***
Normality	1916.000 ***	1439.200 ***	1971.300 ***
Ljung-Box(5)	9.941 *	3.084	9.656 *
Ljung-Box(45)	82.557 ***	61.826 **	75.668 ***

Notes: Returns are calculated as the percentage change in the settlement prices from one day to the next, $R_t = 100(lnP_t - lnP_{t-1})$. CBOT = Chicago Board of Trade. ADF test is the augmented Dickey-Fuller stationarity test with the null hypothesis of a unit root. Normality test is the Jarque-Bera test with the null hypothesis of normally distributed returns. Five lags are used for the ADF; both five and forty-five lags are used for the Ljung-Box test. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

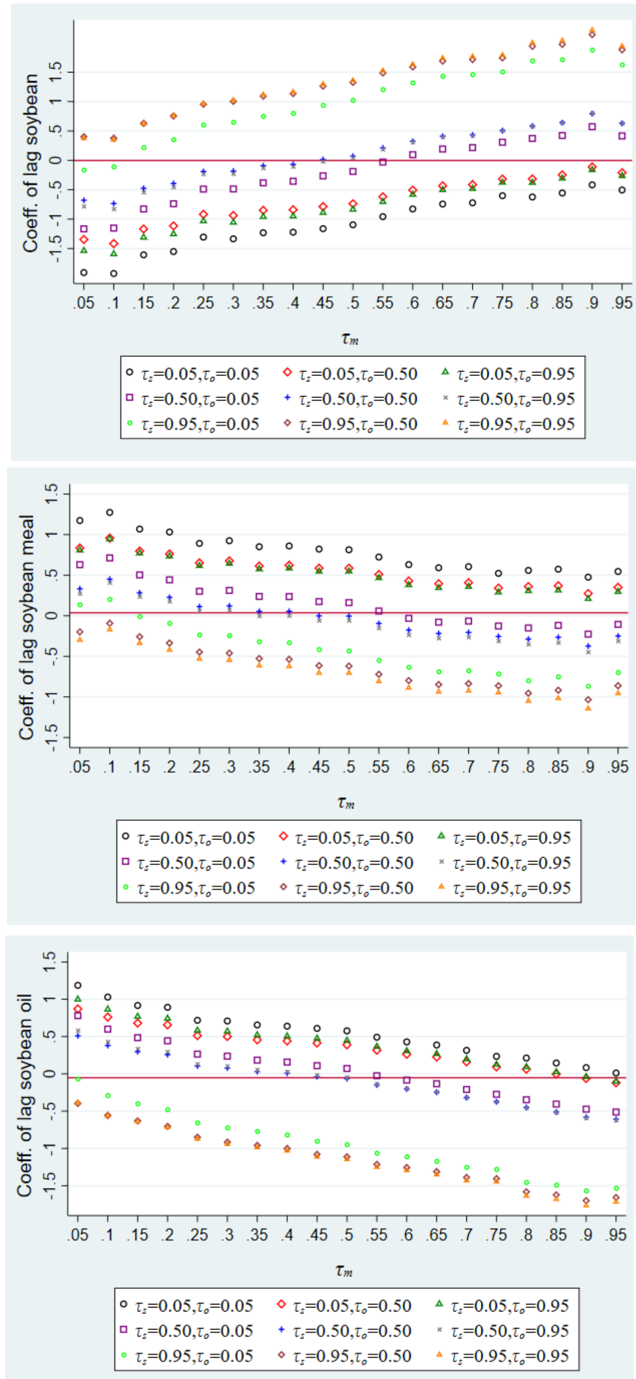


Figure 1. VARQ coefficients for the soybean meal equation

Notes: Own and cross-effects of lagged returns on current soybean meal returns are report at different quantiles $\boldsymbol{\tau} = (\tau_s, \tau_m, \tau_s)', where\ \tau_m \in \{0.05, \dots, 0.95\}$, $\tau_s \in \{0.05, 0.5, 0.95\}$, and $\tau_o = \{0.05, 0.5, 0.95\}$. In addition, the red line shows the OLS estimates of lagged returns.

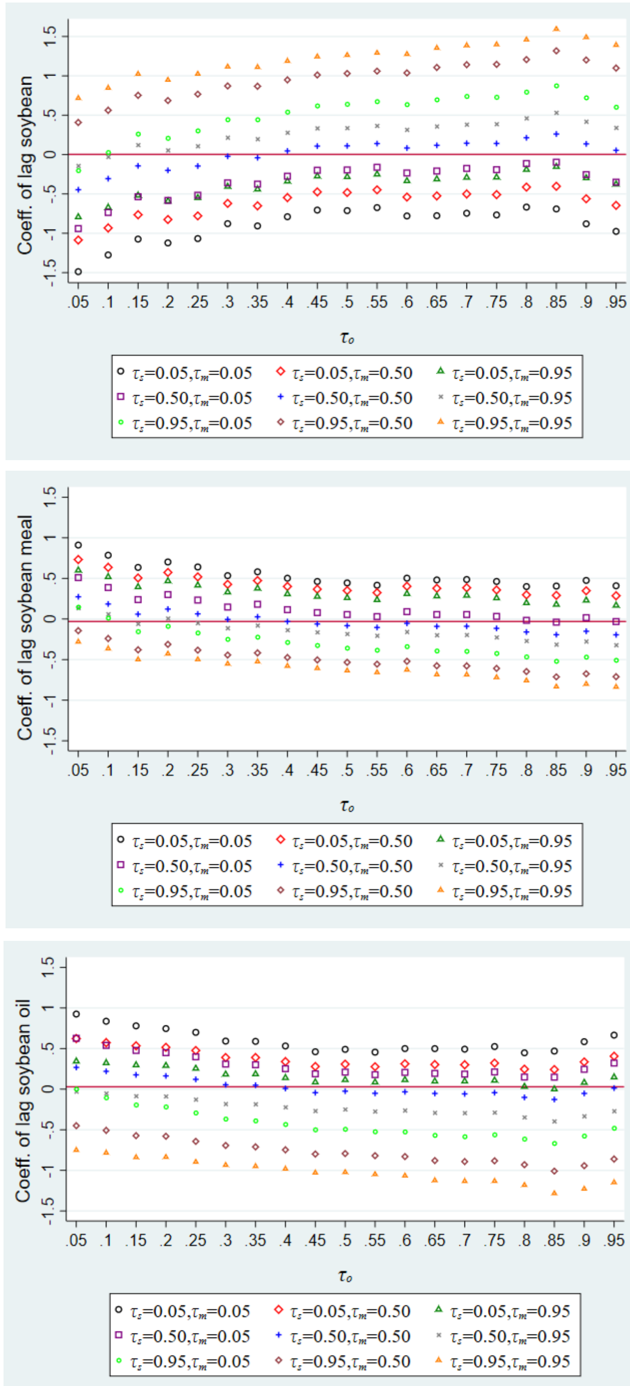


Figure 2. VARQ coefficients for the soybean oil equation
Notes: Own and cross-effects of lagged returns on current soybean oil returns are report at different quantiles $\boldsymbol{\tau} = (\tau_s, \tau_m, \tau_s)', where\ \tau_o \in \{0.05, \ldots, 0.95\}$, $\tau_s \in \{0.05, 0.5, 0.95\}$, and $\tau_m = \{0.05, 0.5, 0.95\}$. In addition, the red line shows the OLS estimates of lagged returns.

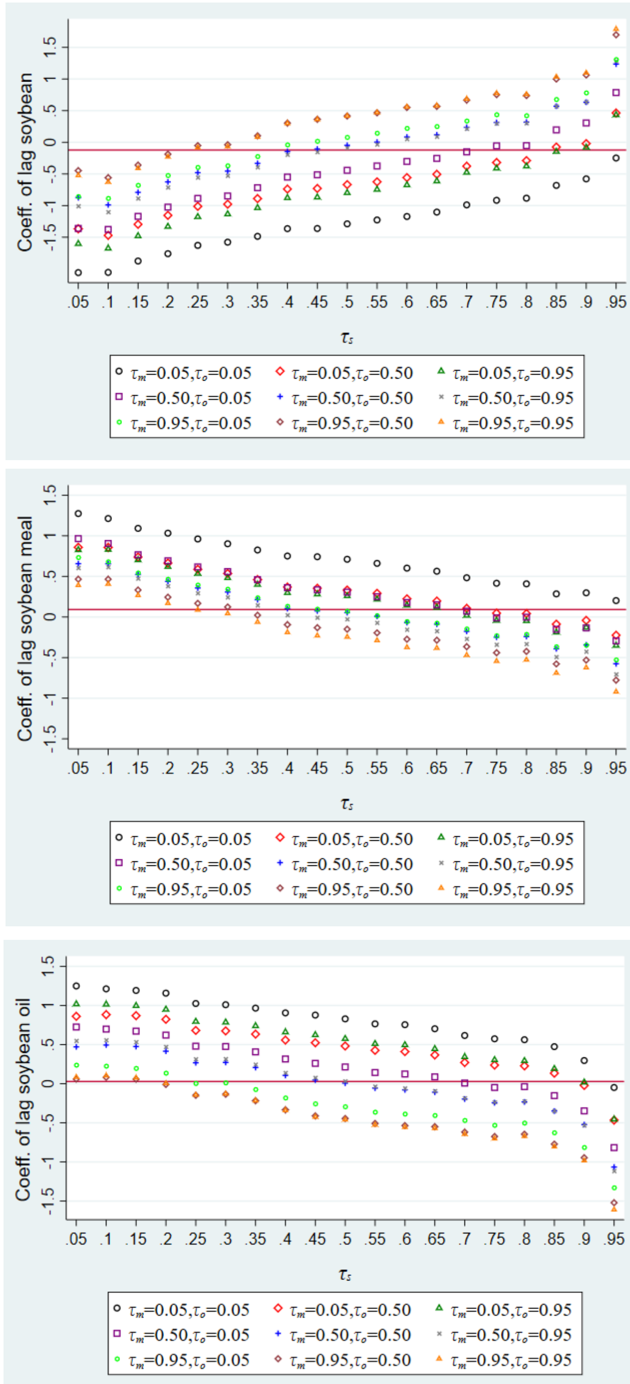
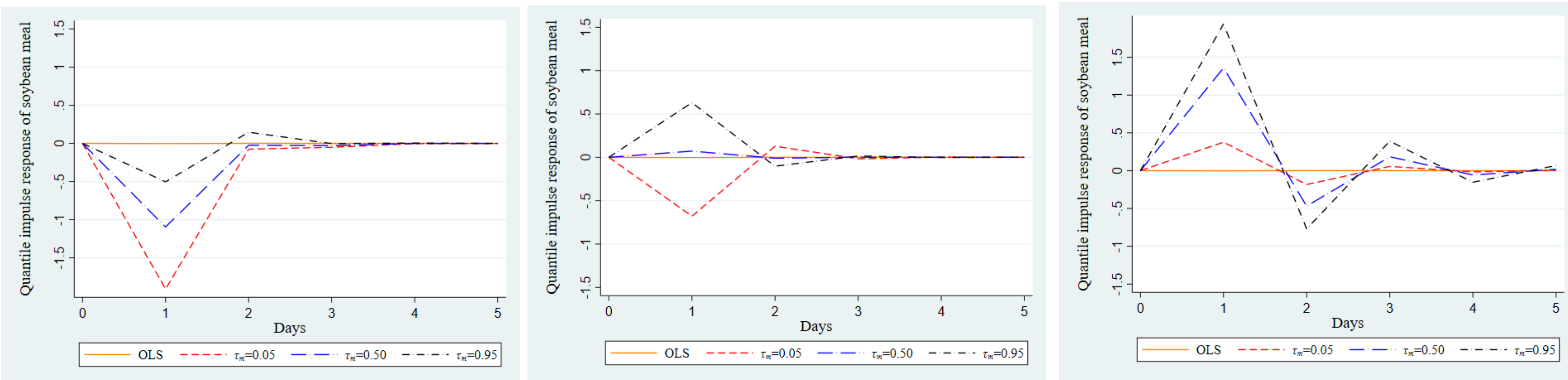


Figure 3. VARQ coefficients for the soybean equation

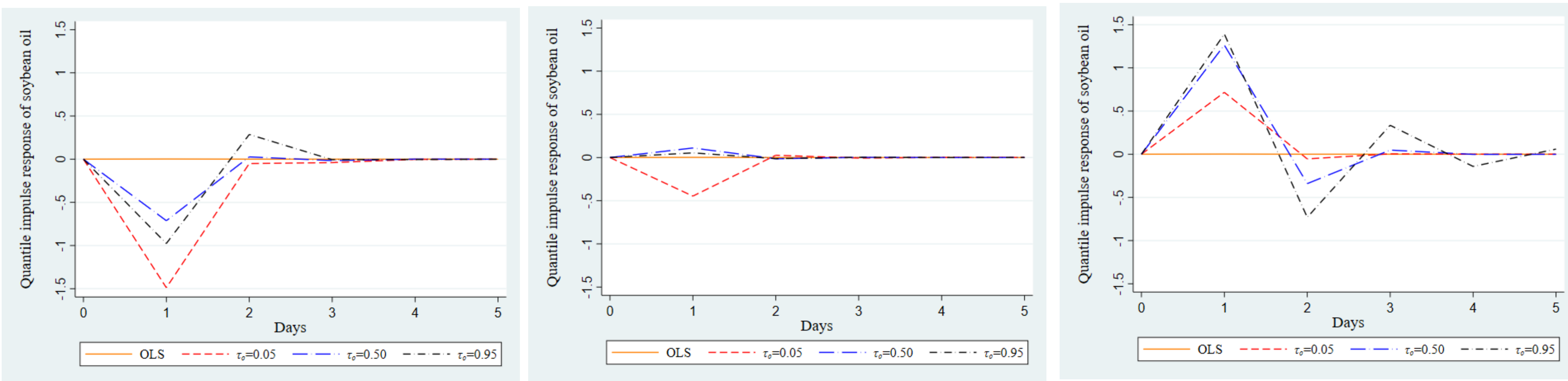
Notes: Own and cross-effects of lagged returns on current soybean returns are report at different quantiles $\boldsymbol{\tau} = (\tau_s, \tau_m, \tau_s)', where\ \tau_s \in \{0.05, \dots, 0.95\}$, $\tau_m \in \{0.05, 0.5, 0.95\}$, and $\tau_o = \{0.05, 0.5, 0.95\}$. In addition, the red line shows the OLS estimates of lagged returns.



(a) $\tau_o = 0.05$, $\tau_s = 0.05$ (b) $\tau_o = 0.5$, $\tau_s = 0.5$ (c) $\tau_o = 0.95$, $\tau_s = 0.95$

Figure 4. Quantile impulse response functions for soybean meal: a unit soybean shock

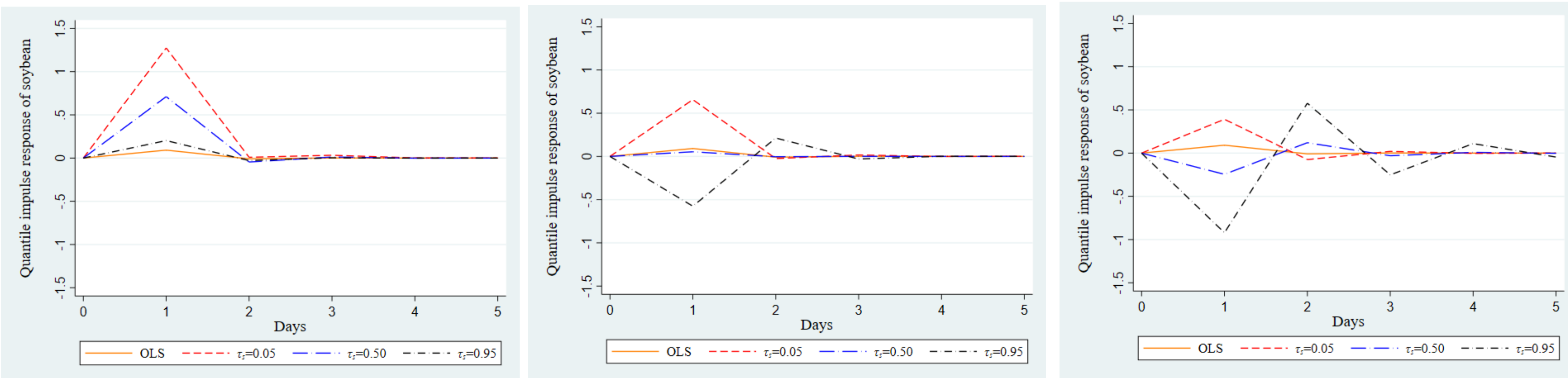
Notes: The impulse responses are the results of a unit shock in the conditional return of soybean market where the shock first occurs. The results are affected by the multivariate quantile vector $\boldsymbol{\tau} = (\tau_s, \tau_m, \tau_o)'$. Days on the horizontal axis refers to the time horizon following the shock. The QIRF changes corresponding to different quantiles of soybean meal, $\tau_m \in \{0.05, 0.5, 0.95\}$ Panel (a) shows the changes in QIRF when the other two commodities are both at low quantiles. Panel (b) shows the changes in QIRF when the other two commodities are both at median quantiles. Panel (c) shows the changes in QIRF when the other two commodities are both at high quantiles.



(a) $\tau_m = 0.05, \tau_s = 0.05$ (b) $\tau_m = 0.5, \tau_s = 0.5$ (c) $\tau_m = 0.95, \tau_s = 0.95$

Figure 5. Quantile impulse response functions for soybean oil: a unit soybean shock

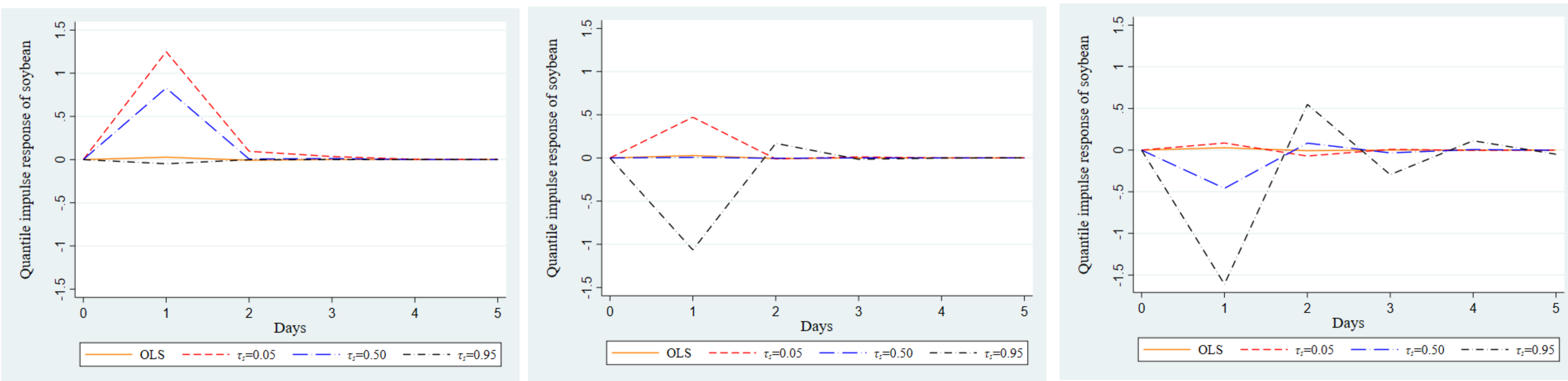
Notes: The impulse responses are the results of a unit shock in the conditional return of soybean market where the shock first occurs. The results are affected by the multivariate quantile vector $\boldsymbol{\tau} = (\tau_s, \tau_m, \tau_o)'$. Days on the horizontal axis refers to the time horizon following the shock. The QIRF changes corresponding to different quantiles of soybean oil, $\tau_o \in \{0.05, 0.5, 0.95\}$ Panel (a) shows the changes in QIRF when the other two commodities are both at low quantiles. Panel (b) shows the changes in QIRF when the other two commodities are both at median quantiles. Panel (c) shows the changes in QIRF when the other two commodities are both at high quantiles.



(a) $\tau_m = 0.05, \tau_o = 0.05$ (b) $\tau_m = 0.5, \tau_o = 0.5$ (c) $\tau_m = 0.95, \tau_o = 0.95$

Figure 6. Quantile impulse response functions for soybean: a unit soybean meal shock

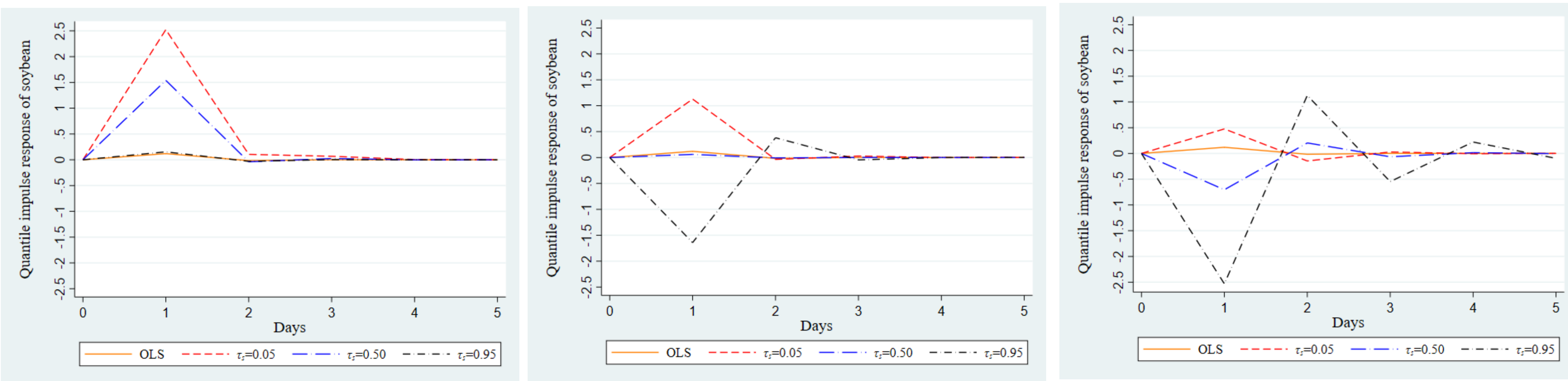
Notes: The impulse responses are the results of a unit shock in the conditional return of soybean meal market where the shock first occurs. The results are affected by the multivariate quantile vector $\boldsymbol{\tau} = (\tau_s, \tau_m, \tau_o)'$. Days on the horizontal axis refers to the time horizon following the shock. The QIRF changes corresponding to different quantiles of soybean, $\tau_s \in \{0.05, 0.5, 0.95\}$ Panel (a) shows the changes in QIRF when the other two commodities are both at low quantiles. Panel (b) shows the changes in QIRF when the other two commodities are both at median quantiles. Panel (c) shows the changes in QIRF when the other two commodities are both at high quantiles.



(a) $\tau_m = 0.05, \tau_o = 0.05$ (b) $\tau_m = 0.5, \tau_o = 0.5$ (c) $\tau_m = 0.95, \tau_o = 0.95$

Figure 7. Quantile impulse response functions for soybean: a unit soybean oil shock

Notes: The impulse responses are the results of a unit shock in the conditional return of soybean oil market where the shock first occurs. The results are affected by the multivariate quantile vector $\boldsymbol{\tau} = (\tau_s, \tau_m, \tau_o)'$. Days on the horizontal axis refers to the time horizon following the shock. The QIRF changes corresponding to different quantiles of soybean, $\tau_s \in \{0.05, 0.5, 0.95\}$ Panel (a) shows the changes in QIRF when the other two commodities are both at low quantiles. Panel (b) shows the changes in QIRF when the other two commodities are both at median quantiles. Panel (c) shows the changes in QIRF when the other two commodities are both at high quantiles.



(a) $\tau_m = 0.05, \tau_o = 0.05$ (b) $\tau_m = 0.5, \tau_o = 0.5$ (c) $\tau_m = 0.95, \tau_o = 0.95$

Figure 8. Quantile impulse response functions for soybean: a unit shock from both soybean meal and oil

Notes: The impulse responses are the results of a unit shock in the conditional return of both soybean meal and oil market where the shock first occurs. The results are affected by the multivariate quantile vector $\boldsymbol{\tau} = (\tau_s, \tau_m, \tau_o)'$. Days on the horizontal axis refers to the time horizon following the shock. The QIRF changes corresponding to different quantiles of soybean, $\tau_s \in \{0.05,0.5,0.95\}$ Panel (a) shows the changes in QIRF when the other two commodities are both at low quantiles. Panel (b) shows the changes in QIRF when the other two commodities are both at median quantiles. Panel (c) shows the changes in QIRF when the other two commodities are both at high quantiles.

Appendix

Table A1. Specifications of CBOT Futures Contracts

Product	First Trading Date	Delivery Months	Price Quotation	Contract Unit
Soybean meal	8/9/1951	Jan., Mar., May, Jul., Aug., Sep., Oct., Dec.	Dollar/ST	100 ST
Soybean oil	7/15/1950	Jan., Mar., May, Jul., Aug., Sep., Oct., Dec.	Cent/lb	60,000 lbs
Soybean	10/5/1936	Jan., Mar., May, Jul., Aug., Sep., Nov.	Cent/bushel	5,000 bushels

Notes: CBOT = Chicago Board of Trade; ST=short ton; lb=pound; 100 ST of soybean meal = 4208 bushels of soybeans; 60000 pounds of soybean oil $\approx$ 5606.402 bushels of soybeans.

Table A2. Summary Statistics of CBOT Futures Prices

	Soybean Meal		Soybean Oil		Soybean	
Mean	5.622		3.369		8.354	
Std. Dev.	1.901		1.239		2.984	
Min	2.702		1.625		4.115	
Max	11.777		7.845		17.683	
Skewness	0.513		1.042		0.736	
Kurtosis	2.317		3.515		2.675	
Observations	7110		7110		7110	
ADF test	-2.216		-2.000		-2.152	
Normality	449.730	***	1365.000	***	672.940	***
Ljung-Box(5)	35266.499	***	35361.350	***	35300.965	***
Ljung-Box(45)	300500.000	***	306100.000	***	302100.000	***

Notes: CBOT= Chicago Board of Trade. ADF test is the augmented Dickey-Fuller stationarity test with the null hypothesis of a unit root. Normality test is the Jarque-Bera test with the null hypothesis of normally distributed returns. Five lags are used for the ADF; both five and forty-five lags are used for the Ljung-Box test. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.