ESSAYS ON PRICE AND VOLATILITY DYNAMICS IN AGRICULTURAL COMMODITY MARKETS

by

YAO YANG

(Under the Direction of Berna Karali)

ABSTRACT

This dissertation consists of three essays on the price behaviors of agricultural commodity markets. It investigates price and volatility dynamics in commodity markets from three aspects: volatility spillover, asymmetric price transmission, and extreme price comovements. The first essay studies volatility transmission between U.S. soybeans and Chinese soybean end products. A bidirectional volatility spillover is found across the two countries, but its effect has decreased since 2009. In addition, the bilateral trade dispute has had a smaller impact on price volatility in futures markets for the soybean complex across countries compared to the 2008 global financial crisis. The second essay applies a multivariate quantile framework to investigate asymmetric price responses in a joint production process. It examines whether output price responses vary with the price levels of other jointly produced goods and under which market conditions asymmetric price transmission might occur. The results show prices of end products respond more to input price increases rather than decreases when their market is bullish and the other product's market is bearish. The third essay studies the relationship between information releases and extreme price movements in related agricultural commodities, including soybean, corn, and wheat. The study examines whether the release of USDA reports has explanatory power for these coexceedances (i.e., more than one market simultaneously suffers from extreme events). After controlling for exposure to other risk factors, most reports increase the probability of return and volatility coexceedances, especially in crop markets.

INDEX WORDS: Asymmetric price transmission, Announcement effects, Coexceedance, Multivariate quantile, Quantile cointegration, Spillover effects, Volatility impulse response

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DEDICATION

I dedicate this dissertation to my loving parents, Feng Yang and Honghua Yao. I grow up with their deep, unconditional, and boundless love. My life journey will end one day, but my gratitude to them will forever endure within the pages of this work.

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CHAPTER 1

INTRODUCTION

Agricultural commodities refer to primary agricultural products in their original forms or with only basic processing, such as soybean, soybean meal, and corn. They are raw materials that support a range of farm-related industries essential for human survival and economic growth, such as food, textile, and biofuel. In 2021, agriculture, food, and related industries accounted for 5.4 percent of the U.S. gross domestic product (GDP) and contributed 10.5 percent to U.S. employment.[1] The importance of agricultural commodities extends beyond their physical uses. Their prices directly affect the incomes of farmers and ranchers (e.g., Tomek and Kaiser 2014; Nigatu et al. 2020). Furthermore, price changes in agricultural inputs can pass through to food-processing costs or food prices. Investigating the pass-through of agricultural prices provides policy implications for the productivity of the agrifood industry and food security (e.g., Morrison Paul and MacDonald 2003; Miller and Coble 2007; Gaigné and Mener 2014).

Price fluctuations are natural characteristics of commodity markets. In particular, agricultural commodity prices are more volatile than the prices of non-farm commodities (Tomek and Kaiser 2014; Declerk 2015). They are influenced by various factors, such as farmers' production strategies and consumers' preferences. On the supply side, agricultural production is vulnerable to weather uncertainty and disease outbreaks, which stimulate price fluctuations. For instance, the 2018 African swine fever outbreak in China, sharply decreased the China's annual

[1] The data are obtained from the U.S. Department of Agriculture, Economic Research Service, Ag and Food Statistics: Charting the Essentials, available at https://www.ers.usda.gov/data-products/ag-and-food-statistics-charting-the-essentials/, on June 19, 2023.

sow inventory by 35% and led to volatile and long-lasting fluctuation of pork prices in the domestic market (Li et al. 2021). On the demand side, changes in consumer preferences and policy regulations bring new challenges for agricultural producers and processors, exacerbating the fluctuation of agricultural commodity prices. For instance, environmental regulations and tax incentives for sustainable biofuels boost U.S. biodiesel production. These policies encourage the demand for crop feedstocks, such as soybean and palm oil, driving their price volatility (CME 2022a). Therefore, unexpected changes in either supply-side or demand-side factors can expose market participants to risks resulting from price fluctuations.

Moreover, price fluctuation in one market can affect the equilibrium prices in other markets. von Cramon-Taubadel and Goodwin (2021) point out, "…arbitrage, or the pursuit of riskless profits, is the underlying economic mechanism that maintains linkages and disciplines departures from equilibrium." When observing an opportunity for arbitrage, rational buyers or sellers will react to eliminate price differences by transferring or transforming the commodity from an unprofitable market to a lucrative one. These two actions refer to two strands in price and volatility transmission. Horizontal price transmission involves price linkages among spatially separated markets where the same commodity is transferred to various locations, while vertical price transmission refers to cases where shocks are transmitted across different stages of supply chains. The first two chapters investigate price relationships among input and its marketable outputs, and the third chapter particularly focuses on the extreme events on price movements of agricultural substitutes. This dissertation investigates price and volatility dynamics from three aspects: volatility spillover, asymmetric price transmission, and extreme price and volatility comovements. Each chapter aims to empirically explore price and volatility dynamics by using advanced econometric models.

The second chapter investigates the responses to shocks in a supply chain across countries since hyper-efficient globalization connects input and output markets in different countries. We use a multivariate GARCH model with a BEKK specification to explore the volatility spillovers between soybeans and their products linked through the cross-border supply chain between the two major players in the global market: the U.S. and China. Given the high dependence of China's soybean crushing industry on soybean imports, we find bidirectional spillovers between the U.S. soybean market and Chinese soybean products, but the cross-volatility spillovers have become weaker after 2009. We also consider the impacts of two significant economic events, the 2008 global financial crisis and the 2018 U.S.-China trade dispute, on volatility spillovers. The key finding shows that volatility significantly responds to the global financial crisis instead of the bilateral trade dispute.

The third chapter considers asymmetric price responses of output prices in a joint production process. We apply a vector error correction quantile (VECQ) framework to fill a gap in the test for price transmission from an input to one of its end products that can be affected by prices of other jointly-produced outputs. Specifically, we investigate price responses to soybean price changes for every possible pair of the quantile indices of soybean end-product prices. The locality of quantiles reflects the characteristic of data clustering within a specific part of the distribution, which reflects the market conditions. Our model reveals that the rockets and feathers pattern, in which output prices respond more to input price increases rather than decreases, exist when one of the soybean end-product's market is bullish whereas the other end-product's market is bearish. In other words, 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 low demand for the other end product (bearish sentiment).

The fourth chapter analyzes whether public information increases the likelihood of extreme price and volatility comovements in related agricultural markets. News and market data releases can trigger sharp price movements leading to financial catastrophes, such as flash crashes. In the context of agricultural markets, such news and market data releases are included in the reports prepared and published by the U.S. Department of Agriculture (USDA). In this chapter, we estimate the likelihood of extreme price and volatility comovements following major USDA reports in the futures markets of three groups of agricultural substitutes: corn-soybean, winter wheat-spring wheat, and lean hog-live cattle-feeder cattle. We use an ordered logistic model to investigate whether the release of USDA reports has explanatory power for these coexceedances (i.e., more than one market simultaneously suffers from extreme events). Our findings contribute to the literature on the market reactions to USDA reports in two aspects. First, we explore the informational value of report clusters on multiple related markets. The June cluster of Acreage and Grain Stocks has the most significant impact on increasing the occurrence of return or volatility coexceedances in grain markets, indicating that these two reports have substantial informational value. Second, we suggest trading strategies for traders holding portfolios of agricultural substitute-commodity derivative instruments following USDA report releases. Although most report clusters have a dual effect, either increasing the probability for portfolio traders to earn or lose money on release days, some of them only impact the occurrence of low returns associated with high volatility. Therefore, corn-soybean traders should avoid holding two contracts together on the release days of the GS report in September, while winter-spring wheat traders should avoid doing so on the release days of PP and GS reports.

In summary, the essays in this dissertation aim to understand the price linkages of related markets linked through a supply chain, which is an important issue for policymakers and producers to evaluate market integration and manage price risks. We list three major policy implications from these findings in Chapter 5.

CHAPTER 2

HOW FAR IS TOO FAR FOR VOLATILITY TRANSMISSION?[2]

[2] Yang. Y., and B. Karali. 2022. *Journal of Commodity Markets* (26): 100198. Reprinted here with permission of publisher.

Abstract

This study investigates the existence of volatility transmission between soybean and its products, which are linked through a cross-border supply chain across the U.S. and China. We estimate a multivariate GARCH model with BEKK specification with daily synchronized returns of the CBOT soybean, DCE soybean meal, and DCE soybean oil futures contracts. To better illustrate the cross-volatility spillovers, we consider volatility transmission across three markets in two subperiods and evaluate the impacts of two significant economic events on price volatility. The estimated results indicate the existence of volatility spillovers to each market from the other two markets. We observe the volatility responses in Chinese soybean product markets to an innovation originating from the U.S. soybean have become weaker after 2009. Moreover, we study the volatility reactions to two significant economic events, the 2008 financial crisis and 2018 U.S.-China trade dispute, but the volatility reactions can only be found in the financial crisis.

Introduction

Supply chains are inherently susceptible to risks. Earlier studies stressed the importance to investigate the risks arising from unintended change of flows related to products, information, and money in supply networks (Kraljic 1983; Treleven and Schweikhart 1988; Tang 2006). With the development of global trades, the international labor division expands national supply networks to the worldwide. Value-added processing links input and output markets located in different countries. A product is not only consumed in the domestic market, but can also be sold as an intermediate good to foreign markets. The international interdependence of these valued-added processing ultimately leads to the vulnerability of supply chains to risks (Wagner and Bode 2009).

Price shock is an important source of operational risks in agricultural supply chains. Vavra and Goodwin (2005) point out that the adjustment to price shocks along the supply chain is an integral part of well-functioning markets and therefore, agricultural economists as well as policy makers have been greatly interested in understanding volatility transmission through the supply chain. An extensive literature exists on volatility spillover effects along a supply chain within a country (Apergis and Rezitis 2003; Karali and Ramirez 2014; Chavas and Pan 2020), or through related markets in different regions or countries (Ceballos et al. 2017; Dahl and Jonsson 2018; Bronnmann et al. 2020).

Recent research has realized a more complex aspect of price transmission and explored the extent to which products are linked within a cross-border supply chain (Balaguer 2011; Landazuri-Tveteraas et al. 2018; Auer, Levchenko, and Sauré 2019). However, few papers empirically investigate the volatility transmission and responses to price shocks in a supply chain across countries. This could be because an input imported from a foreign market has an ambiguous price relation to its value-added commodities produced in the domestic market. Moreover, lower frequency of retail or wholesale price data might be limiting a further discussion on volatility transmission along the cross-border supply chain. To deal with these two issues, the goal of this paper is to use high-frequency data from futures markets to investigate volatility transmission between soybean and its products (soybean meal and oil), which are linked in a cross-border supply chain between the U.S. and China.

As detailed in the next section, China's soybean crushing industry heavily depends on soybean imports, resulting in a strong linkage between the U.S. soybean and Chinese soybean products. In addition, futures markets facilitate efficient transfer of price risks among commercial and non-commercial users of commodities and are shown to lead spot markets in price discovery (Garbade and Silber 1983; Zapata and Fortenbery 1996; Theissen 2012). Hence, a thorough understanding of volatility spillovers among trading partners provides a new perspective for market participants to understand the price relations between upstream and downstream products in a global supply chain.

Moreover, the 2008 global financial crisis and the 25% retaliatory tariff imposed by China on the U.S. soybean during the period of 2018 U.S.-China trade dispute, provide us an opportunity to discuss the impacts of economic and financial events on volatility transmission in the soybean complex (soybean, soybean oil, and soybean meal) across two countries. To this end, we use a multivariate generalized autoregressive conditional heteroskedasticity framework with BEKK (Baba-Engle-Kraft-Kroner) specification with exogenous factors in the conditional variance equations, MGARCH-X-BEKK, using synchronized daily (close-to-close) returns of the Chicago Board of Trade (CBOT) soybean, Dalian Commodity Exchange (DCE) soybean meal, and DCE soybean oil futures contracts.[3] Our study contributes to the understanding of the volatility spillover effects in a cross-border supply chain in four ways. First, we test and confirm the existence of spillover effects among the U.S. soybean and China's soybean meal and oil markets. Second, we show that directions of volatility spillovers between soybean and soybean meal are different from those between soybean and soybean oil. Third, we show that these spillover effects become much weaker in the current years once we account for the structural break in 2009. Fourth, we show that a global recession spikes price volatility in downstream markets more severely than a bilateral trade conflict does.

Soybean Complex across the U.S. and China

To accurately measure volatility spillover effects, it is very important to understand the strong connection among soybean products in the U.S. and China. We review the study of horizontal (i.e., spatial) and vertical price relationships in soybean complex across these two countries and explain the strong connection between U.S. soybean and Chinese soybean products.

Global soybean trade is highly concentrated geographically with three countries: China, the United States, and Brazil. China accounted for 64.79% of global soybean imports, and Brazil and the U.S. together supplied 85.35% of global exports in 2018.[4] China is not only the world's largest soybean importer, but also the largest market for the U.S. soybean export. Before the U.S.-China trade dispute in 2018, China spent over $10 billion on purchasing the U.S. soybean

[3] Since the U.S. and Chinese futures markets have different trading hours, we synchronize the DCE soybean meal and oil returns with the CBOT soybean return.
[4] The data source for soybean import and export is from UN Comtrade Database, retrieved from https://comtrade.un.org/data/.

since 2010, which accounted for over half of the trade value for total U.S. soybean export. No country like China has such a large share of imports in both global and local soybean trade. The size of soybean market and the rapid growth in its future demand made soybean a focus of attention when China imposed a 25% retaliatory tariff on the U.S. soybean in the summer of 2018 (Muhammad and Smith 2018; Sabala and Devadoss 2019; Ji, Zhang, and Zhu 2020).

Price and volatility transmission across the U.S. and China soybean markets have long been a question of interest for researchers. An extensive literature has investigated spatial price linkages focusing on price and volatility transmission across the U.S. and Chinese soybean futures markets. Their findings provide ample evidence that soybean futures contracts traded at the CBOT and DCE are cointegrated in the long term. While earlier studies found volatility spillovers only from the CBOT futures market to the DCE (Fung, Leung, and Xu 2003; Hua and Chen 2007), more recent studies found bidirectional but asymmetric volatility spillover effects across the two markets (Liu and An 2011; Han, Liang, and Tang 2013; Jiang et al. 2016).

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. Previous studies have investigated vertical price linkages by focusing on price and volatility transmission between soybean and its products, soybean meal and oil, either in the U.S. or in the Chinese futures market. In the U.S. futures market, price comovements in the soybean complex are found (Rausser and Carter 1983); furthermore, the price correlations in the soybean complex are utilized in the studies of hedging strategies (Garcia, Roh, and Leuthold 1995; Tejeda and Goodwin 2014), the economic value of public information (Karali 2012), and arbitrage opportunities for the soybean crush spread (Johnson et al. 1991; Simon 1999; Mitchell 2010; Marowka et al. 2020). On the other hand, futures prices of the Chinese soybean complex are cointegrated in the long run (Li and Zhang 2011; Fung et al. 2013). Moreover, volatility spillovers and correlations are also found among soybean, soybean meal and oil futures traded at the DCE (Liu and Sono 2016; Ruan, Cui, and Fan 2020).

However, few papers discuss price relationships between the U.S. soybean and China's soybean meal and oil, which are linked through the supply chain in the global market. In fact, Chinese soybean imports are driven by demand for animal protein and edible oils; nearly all soybean imports are used to produce high-protein meals for livestock and cooking oil for food consumption (Gale, Valdes, and Ash 2019). The high dependence of China's soybean crushing industry on soybean imports is a result of (1) rapid growth in food consumption, (2) tariff structure in the soybean complex, and (3) the domestic policy for genetically modified organism (GMO) soybean. Rising living standards has spurred a diversifying Chinese diet composed of high-protein meal and edible oil since 1990. Soybean meal is the second major raw material in animal feed (Gale 2015); soybean oil is the primary vegetable oil accounting for more than 40% of total oil consumption in China.[5] Although China is the world's fourth-largest producer of soybean, rapid growth of high-protein food consumption turned the country into the world's largest soybean importer (Gale, Valdes, and Ash 2019). China's tariff structure favored imports of soybean. Before implementation of the retaliatory soybean tariff, China's most favored nation (MFN) tariff on soybean imports was 3%, which is the lowest compared to 9% MFN tariff for soybean oil and 5% MFN tariff for soybean meal (Gale 2015; Gale, Valdes, and Ash 2019). GMO soybean has advantages with low production costs but high quality for oil crushing and a

[5] The data source for China's oil consumption is from a USDA's monthly report *Oilseeds: World Markets and Trade*, published on November 8, 2019, retrieved from https://usda.library.cornell.edu/concern/publications/tx31qh68h?locale=en.

high-protein source for animal feed, and it has been widely used in Chinese soybean crushing industry. Although China has been importing GMO soybean since 1997 and permitted its use as an input for soybean crushing in 2004, China has not yet approved any GMO soybeans for domestic cultivation. However, the government has been working on the commercialization of GMO soybeans for indirect food use. The number of biosafety certificates for imported GMO soybeans as processing materials has increased from one in 2004 to nineteen in 2021.[6] This provides a legal support to vary the species of GMO soybeans and further opens China's market to imported GMO soybeans.

As indicated previously, a strong connection exists between China's soybean import and its domestic production of soybean meal and oil. This connection motivates our study of volatility transmission between the Chinese soybean meal and oil futures markets and the U.S. soybean, the second largest source of China's soybean import.[7]

Data Construction and Asynchronous Trading Problem

Futures contracts and price series

We use futures contracts traded at the CBOT and DCE. CBOT, the world's largest grains futures market, provides the most active and liquid U.S. soybean futures contracts. These contracts have seven delivery months with a standard contract size of 5,000 bushels and the price is quoted in

[6] Exporters of GMO soybean to China should obtain a biosafety certificate issued by the Ministry of Agricultural and Rural Affairs of China (MARA). The validity of period for both the new and renewed certificates varies from three to five years depending on China's regulatory system. The list of approved biotechnology products is annually updated on the official website of MARA (http://www.moa.gov.cn/ztzl/zjyqwgz/spxx/index.htm). Using this list, we counted the number of approved GMO soybean certificates that are valid until 2021.

[7] U.S. has not been the largest soybean supplier for China since 2013, but it still has been occupying a large share of China's soybean imports. For example, Brazil exported 38.21 MMT (million metric tons) soybean to China in 2016, constituting 45.5% of the Chinese soybean market, while the U.S. exported 34.17 MMT soybean with a 40.7% share.

U.S. cents per bushel. On the other hand, DCE is the largest and most active futures market for soybean meal and oil in China. Both contracts have eight delivery months with contract sizes of 10 metric tons (MT) and the prices are quoted in Yuan per MT. Table 1 shows specifications for these three futures contracts in detail.

Our futures price data are obtained from Bloomberg covering the period from January 18, 2006 to December 31, 2019. 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.[8] We create nearby CBOT soybean 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 DCE soybean meal and oil contracts that expire two to four months later than the soybean contract while excluding the contracts that are highly illiquid (March, July, August, November, and December contracts).[9] The resulting price series are nonstationary, have heteroskedastic variance, and exhibit ARCH effects.[10]

Asynchronous and synchronous close-to-close returns

Asynchronization is an important issue when studying price or volatility transmission and

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[8] We use daily data on currency exchange rates from the Federal Reserve Bank of St. Louis. The conversion of soybean meal and oil to soybean follows the rules published by the U.S. Soybean Export, retrieved from https://ussec.org/resources/conversion-table/.

[9] Table A.1 in the appendix lists the specific futures contracts used in each calendar month to construct futures price series.

[10] Table A.2 in the appendix shows summary statistics of the resulting futures price series. The average price for DCE soybean meal, soybean oil, and CBOT soybean are $9.63/bushel, $5.23/bushel, and $10.62/bushel, respectively. The U.S. soybean futures price has the largest standard deviation of 2.52, while the standard deviation of the Chinese soybean oil price is the lowest, 1.30. 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 homoskedasticity in all price series, indicating they have heteroskedastic variances. While the DCE soybean meal price is normally distributed, the DCE soybean oil and CBOT soybean prices are not. Moreover, we reject both null hypotheses of no ARCH effects and no autocorrelation in all price series.

correlations between futures markets with different trading hours. Asset prices will be stale after futures markets close, and the use of stale prices in calculating close-to-close returns would distort the value of portfolio and value at risk measures (Burns, Engle, and Mezrich 1998). Figure 1 illustrates the asynchronous trading hours in China and the U.S.[11] The daytime trading hours in DCE is from 9:00 am to 11:30 am and from 1:30 pm to 3:00 pm in Beijing time, while the nighttime trading hours are from 9:00 pm to 11:30 pm.[12] CBOT is open from 8:30 am to 1:20 pm and its overnight trading hours are from 7:00 pm to 7:45 am in Central Standard Time (CST). Beijing is 13 hours ahead of CST during the standard periods, and it is 14 hours ahead during the daylight savings.[13]

The Chinese futures market closes first, followed by the U.S. soybean futures market. Therefore, while the U.S. futures contracts are being traded, the DCE prices remain the same, becoming stale. As seen in figure 1, the DCE's asynchronous close-to-close return on day t, R_t, calculated using stale closing prices from day t-1 to t, partially overlaps with the CBOT's close-to-close return on the same day. However, "fresh" futures prices can be estimated even when the DCE is closed by using the information from the markets that are open. Therefore, we use the information from the U.S. soybean market as an anchor of synchronization to estimate what the DCE prices would be if the markets were open. As a result, the CBOT's close-to-close soybean return remains unchanged, and the DCE's returns are synchronized by predicting the unobserved returns that would have been observed from the closing time of DCE to the closing time of

[11] For brevity, we only plot daytime trading hours as we use settlement prices for the daytime trading sessions to calculate daily close-to-close returns.
[12] DCE provides overnight trading since 2014 and adjusts the nighttime hours based on trading demand. For example, due to the outbreak of COVID-19, DCE cancelled the overnight trading from February 3, 2020 to May 6, 2020.
[13] However, daylight savings periods neither affect the measurement of returns nor the synchronization process.

CBOT on day t. Specifically, using the notation in figure 2.1, the synchronized return in DCE can be written as:

$$(2.1)\quad R_t^S = R_t - \xi_{t-1} + \xi_t,$$

where R_t is the observed, asynchronous return in DCE on day t and ξ_t is the unobserved return when the DCE is closed. In other words, the synchronized return equals to the asynchronous return plus a correction.

We follow Audrino and Bühlmann (2004) and Hernandez, Ibarra, and Trupkin (2014) to predict the correction for synchronized returns. Let $P_{i,t}$ denote the closing price of commodity i on day t, where i = M (DCE soybean meal), O (DCE soybean oil), and S (CBOT soybean). We define the asynchronized returns as the percent change in the asynchronized prices, $R_{i,t} = 100 \times (\ln P_{i,t} - \ln P_{i,t-1})$. Analogously, the synchronized returns are measured as $R_{i,t}^s = 100 \times (\ln P_{i,t}^s - \ln P_{i,t-1}^s)$. The expected price on day t+1 is an unbiased estimator of the synchronized price on day t, $\ln P_{i,t}^s = E(\ln P_{i,t+1} \,|I_t)$, where I_t is the information set at t (Hernandez, Ibarra, and Trupkin 2014). Therefore, the synchronized returns are written as

$$\begin{aligned}(2.2)\ R_{i,t}^s &= 100 \times \left[E_t\left(\ln P_{i,t+1} \,|I_t\right) - E_{t-1}\left(\ln P_{i,t} \,|I_{t-1}\right)\right] \\ &= 100 \times \left[E_t\left(\ln P_{i,t+1} - \ln P_{i,t} \,|I_t\right) - E_{t-1}\left(\ln P_{i,t} - \ln P_{i,t-1} \,|I_{t-1}\right) + \ln(P_{i,t}/P_{i,t-1})\right] \\ &= R_{i,t} + E_t\left(R_{i,t+1}\middle|I_t\right) - E_{t-1}\left(R_{i,t}\middle|I_{t-1}\right).\end{aligned}$$

The sum of the second and third term in equation (2.2), $E_t\left(R_{i,t+1}\middle|I_t\right) - E_{t-1}\left(R_{i,t}\middle|I_{t-1}\right)$, represents the correction for calculating the synchronized returns. To calculate this correction, we need a model that not only provides these expected returns with a given information set at any time, but also the covariance matrix of all returns (Burns, Engle, and Mezrich 1998).

GARCH models are the most popular in the application for the synchronization of financial asset prices (Audrino and Bühlmann 2004; Hernandez, Ibarra, and Trupkin 2014; Happersberger, Lohre, and Nolte 2020). A GARCH model is also supported for the U.S.-China soybean complex based on the Lagrange multiplier tests for ARCH effects in the return series given in table 2.2.

We denote $\mathbf{R}_\mathrm{t}$ as the vector of asynchronized close-to-close returns in each market and $\mathbf{R}_\mathrm{t}^\mathrm{s}$ as the vector of synchronized returns. Based on the Akaike information criterion (AIC), we use a vector autoregressive (VAR) model with four lags to estimate the asynchronous returns in each market in a trivariate matrix format as follows:

$$(2.3)\quad \mathbf{R}_\mathrm{t} = \boldsymbol{\mu} + \boldsymbol{\lambda}_1\mathbf{R}_{\mathrm{t}-1} + \boldsymbol{\lambda}_2\mathbf{R}_{\mathrm{t}-2} + \boldsymbol{\lambda}_3\mathbf{R}_{\mathrm{t}-3} + \boldsymbol{\lambda}_4\mathbf{R}_{\mathrm{t}-4} + \boldsymbol{\epsilon}_\mathrm{t}, \qquad \boldsymbol{\epsilon}_\mathrm{t}|\mathrm{I}_{\mathrm{t}-1} \sim MVt_v(\mathbf{0}, \boldsymbol{\Sigma}_\mathrm{t}),$$

where $\boldsymbol{\mu}$ is a vector of constants, $\boldsymbol{\lambda}_\mathrm{j}$ is the matrix of VAR coefficients for lagged returns with lag j. $\boldsymbol{\epsilon}_\mathrm{t}$ is a 3×1 vector of error terms with zero conditional mean based on past information I_{t-1}, and conditional time-varying variance-covariance matrix $\boldsymbol{\Sigma}_\mathrm{t}$. Considering the leptokurtic nature of asynchronous return distributions shown in table 2, we assume the error terms follow a multivariate Student's *t* distribution with degrees of freedom, v. Given this VAR(4) structure of the asynchronous returns, equation (2.2) can be rewritten as:

$$\begin{aligned}(2.4)\quad \mathbf{R}_\mathrm{t}^s &= \mathbf{R}_\mathrm{t} + E_\mathrm{t}(\mathbf{R}_{\mathrm{t}+1}|\mathrm{I}_\mathrm{t}) - E_{\mathrm{t}-1}(\mathbf{R}_\mathrm{t}|\mathrm{I}_{\mathrm{t}-1}) \\ &= \mathbf{R}_\mathrm{t} + \boldsymbol{\Gamma}_1(\mathbf{R}_\mathrm{t} - \mathbf{R}_{\mathrm{t}-1}) + \boldsymbol{\Gamma}_2(\mathbf{R}_{\mathrm{t}-1} - \mathbf{R}_{\mathrm{t}-2}) + \boldsymbol{\Gamma}_3(\mathbf{R}_{\mathrm{t}-2} - \mathbf{R}_{\mathrm{t}-3}) + \boldsymbol{\Gamma}_4(\mathbf{R}_{\mathrm{t}-3} - \mathbf{R}_{\mathrm{t}-4}).\end{aligned}$$

Following Audrino and Bühlmann (2004), we set up the structure of the VAR coefficient matrices, $\boldsymbol{\Gamma}_\mathrm{j}$, with two sets of constraints. First, as the CBOT trading time is the anchor of synchronization, the coefficients of the DCE's returns on the CBOT soybean return are set to zero. Second, we set the elements of matrix $\mathbf{\Gamma}_j$ to zero if they are not statistically significant at the 5% level. After imposing these constraints, we re-estimate the VAR(4)-MGARCH(1,1) model to obtain the parameter estimates, $\hat{\mathbf{\Gamma}}_j$, and calculate the synchronized returns as equation (2.4).

Table 2.2 also reports summary statistics of daily synchronized returns. The mean of synchronized return is very similar to that of the original, asynchronous return for both soybean meal and oil. However, the variance is typically larger for both synchronized returns because of the unobservable changes in the period between the closing times of DCE and CBOT. These findings are consistent with the results in previous studies applying the synchronization method (Burns, Engle, and Mezrich 1998; Happersberger, Lohre, and Nolte 2020). The correlations across global markets are underestimated by using asynchronous returns (Martens and Poon 2001; Schotman and Zalewska 2006; Hernandez, Ibarra, and Trupkin 2014). We show the Pearson correlation coefficients among the three returns in table 2.3, and our results find evidence of increased correlations after synchronizing the returns. The correlation between the DCE soybean meal and CBOT soybean increases from 0.238 to 0.729 after synchronization, and the correlation between the DCE soybean oil and CBOT soybean increases from 0.222 to 0.615. Synchronization corrects the underestimation of correlations and allows us to analyze the spillover effects across markets when information is flowing. Moreover, the correlation is a simplistic measure of market integration (Goetzmann, Li, and Rouwenhorst 2005; Aityan, Ivanov-Schitz, and Izotov 2010), and therefore these increased correlations reflect to some degree the market integration between the U.S. and China's markets.

Estimation Methodology

As shown in table 2.2, all synchronized returns (synchronized CBOT returns are the same as the asynchronous returns as CBOT is used as an anchor for synchronization) exhibit heteroskedasticity. Moreover, the existence of ARCH effects cannot be rejected in any of the return series, suggesting a time-varying variance. This time-varying variance represents the risk level of a return series, which can be predicted by the past squared residuals (ARCH terms) and variance of residuals (GARCH terms). When dealing with more than one series, multivariate GARCH models are commonly used to capture time-varying volatilities and dynamic patterns in the joint distribution of daily futures returns. To determine the volatility transmission in the soybean complex across countries, we use a MGARCH model with BEKK specification and with exogenous factors in the conditional variance equations, MGARCH-X-BEKK. These exogenous factors are dummy variables for two important events, the 2008 global financial crisis and 2018 U.S.-China trade dispute, which might have an impact on the conditional volatility.[14] The advantage of the BEKK specification is its flexibility to estimate spillover effects of both ARCH and GARCH terms in the conditional variance and covariance equations.

The 3×1 vector $\mathbf{R}_t^s$, defined as before, consists of the synchronized close-to-close returns in each market *i*, where *i* = *M*, *O,* and *S*, representing DCE soybean meal, DCE soybean oil, and CBOT soybean, respectively. Based on the AIC, we fit a VAR(2) model to the daily

[14] We define the period for global financial crisis from December 2007 to June 2009 based on the U.S. Business Cycle and Contractions from NBER, retrieved from https://www.nber.org/cycles.html. On the other hand, we define the period for trade dispute from April 4, 2018, the date Chinese government announced 25% retaliatory tariff on U.S. goods, to December 31, 2019.

synchronized returns with residuals modeled as a MGARCH-X(1,1) process. Consider the trivariate VAR(2) model for synchronized returns in matrix form given by:

$$(2.5) \quad \mathbf{R}_{\mathrm{t}}^{\mathrm{s}} = \boldsymbol{\mu} + \boldsymbol{\theta}_{\mathbf{1}}\mathbf{R}_{\mathrm{t}-1}^{\mathrm{s}} + \boldsymbol{\theta}_{\mathbf{2}}\mathbf{R}_{\mathrm{t}-2}^{\mathrm{s}} + \boldsymbol{\varepsilon}_{\mathrm{t}},$$

where $\boldsymbol{\varepsilon}_{\mathrm{t}}$ is a 3×1 vector of regression error terms following a multivariate Student's *t* distribution with zero mean, variance $\mathbf{H}_{\mathrm{t}}$, and degrees of freedom η, $\boldsymbol{\varepsilon}_{\mathrm{t}} \sim MVt_{\eta}(\mathbf{0}, \mathbf{H}_{\mathrm{t}})$.[15] The conditional variance-covariance matrix in the BEKK specification is defined as:

$$(2.6) \quad \mathbf{H}_{\mathrm{t}} = \mathbf{C}'\mathbf{C} + \mathbf{A}'\boldsymbol{\varepsilon}_{\mathrm{t}-1}\boldsymbol{\varepsilon}_{\mathrm{t}-1}'\mathbf{A} + \mathbf{B}'\mathbf{H}_{\mathrm{t}-1}\mathbf{B} + \sum_{\boldsymbol{k}=\mathbf{1}}^{K} \mathbf{G}_{\boldsymbol{k}}'\mathbf{G}_{\boldsymbol{k}}\mathbf{X}_{\boldsymbol{k},\boldsymbol{t}},$$

where $\mathbf{H}_{\mathrm{t}}$ is a 3×3 symmetric matrix with variances of residuals on the diagonal and covariances off the diagonal, **C** is a 3×3 low triangular matrix of constants, **A** and **B** are 3×3 full matrices of ARCH and GARCH parameters, respectively. $\mathbf{G}_{\boldsymbol{k}}$ is a 3×3 low triangular coefficient matrix on the dummy variables $\mathbf{X}_{\boldsymbol{k},\boldsymbol{t}}$. Specifically, the matrices are defined as follows:

$$(2.7) \quad \mathbf{H}_{\mathrm{t}} = \begin{bmatrix} h_{MM,t} & h_{MO,t} & h_{MS,t} \\ h_{MO,t} & h_{OO,t} & h_{OS,t} \\ h_{MS,t} & h_{OS,t} & h_{SS,t} \end{bmatrix}, \ \mathbf{C} = \begin{bmatrix} c_{MM} & 0 & 0 \\ c_{OM} & c_{OO} & 0 \\ c_{SM} & c_{SO} & c_{SS} \end{bmatrix}, \ \mathbf{G}_{\boldsymbol{k}} = \begin{bmatrix} g_{k,MM} & 0 & 0 \\ g_{k,OM} & g_{k,OO} & 0 \\ g_{k,SM} & g_{k,SO} & g_{k,SS} \end{bmatrix},$$

$$\mathbf{A} = \begin{bmatrix} a_{MM} & a_{MO} & a_{MS} \\ a_{OM} & a_{OO} & a_{OS} \\ a_{SM} & a_{SO} & a_{SS} \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} b_{MM} & b_{MO} & b_{MS} \\ b_{OM} & b_{OO} & b_{OS} \\ b_{SM} & b_{SO} & b_{SS} \end{bmatrix},$$

where, as before, the subscripts *M*, *O*, and *S* denote the DCE soybean meal, DCE soybean oil, and CBOT soybean futures, respectively. In the BEKK specification, the variances ($h_{MM,t}$,

[15] As shown in table 2.2, all synchronized returns reject the normality. Therefore, we assume the error terms follow a multivariate Student's *t* distribution in the MGARCH-X-BEKK model.

$h_{OO,t}$, $h_{SS,t}$) and the covariances ($h_{MO,t}$, $h_{MS,t}$, $h_{OS,t}$) involve several combinations of the estimated parameters in matrices $\mathbf{C}$, $\mathbf{A}$, $\mathbf{B}$ and $\mathbf{G}_{\boldsymbol{k}}$, which are provided in the appendix.

Intuitively, MGARCH-X(1,1) describes a dynamic path of price volatility in each commodity market. The variance of returns in the next period is a weighted average of the new information captured by the most recent squared residuals (ARCH term), the variance for the current period (GARCH term), and the long-run average variance (constant term) (Engle 2001). It can also be thought of as an adaptive updating mechanism for traders in adjusting their prediction on the risk level of returns based on the existing residuals and variances of residuals.

Results

We first present the estimation results using the full sample, and then show the results for two different sample periods determined by a structural break, which possibly occurred due to changes in the trading environment between two countries. To better illustrate volatility spillovers, we perform volatility impulse response analyses to trace the effects of own- and cross-market shocks in each market.

Base results for the full sample

Full sample results are presented in table 2.4 for the conditional mean equations and in table 2.5 for the conditional variance equations.[16,17] The spillover and exogeneity tests (Wald type joint exclusion tests) are provided in the bottom part of both tables.

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[16] For brevity, we do not provide the estimation results for covariance equations; however, they are available from authors upon request.

[17] Model diagnostics tests are provided in the appendix table A.3. The estimated degrees of freedom are small, further supporting the use of multivariate Student's t distribution. Based on the Ljung-Box test and multivariate Q statistics, we fail to reject independence of the standardized residuals. Moreover, based on the Lagrange Multiplier (LM) tests with 5 and 25 lags, we fail to reject the null hypothesis of no ARCH effects for all three squared standardized residuals.

Estimation results in table 2.4 show that daily returns of all commodities have a first-degree autocorrelation. It appears that while the serial correlation in the DCE soybean meal and oil futures returns is positive, it is negative for the U.S. soybean returns. This can be explained from substitution effects in the demand. A high return for the U.S. soybean indicates an increase in the production costs for soybean crushing, which dampens the demand for imported soybean and raises demand for substitutes of soybean products, such as palm oil and corn, leading to lower soybean returns in the next period. Spillover tests reject for all three commodities the null hypothesis of no return spillover from the other markets. A return spillover from the U.S. soybean market to the Chinese soybean meal and oil markets is supported by the significant second lag of the U.S. soybean returns in meal and oil equations. On the other hand, the second lags of Chinese soybean meal and oil returns also significantly affect the U.S. soybean returns implying a return spillover from Chinese markets to the U.S. market.

Turning to the conditional variance equations in table 2.5, the coefficients on own-ARCH and GARCH terms (a_{ii} and b_{ii}, i=M, O, S) are statistically significant and larger than the cross coefficients in all three markets. More specifically, the U.S. soybean market has a higher own-ARCH coefficient than Chinese markets, but it has the lowest GARCH coefficient among three markets. This suggests, compared to Chinese markets, the own shocks in the U.S. soybean market have a relatively significant but short-term effect on its return volatility, while its own volatility shocks have a lower level of persistence. Regarding the cross coefficients, the cross-ARCH coefficients (a_{ij}, i,j=M, O, S and $i \neq j$) capture the direct effects of lagged innovations from market i to the current conditional variance in market j, while the cross-GARCH coefficients (b_{ij}) capture the direct dependence of volatility in market j on that of market i.

These cross- coefficients are statistically significant except two cross-ARCH (a_{MO} and a_{SM}) and one cross-GARCH (b_{MO}) estimates.

The suitability of using a non-diagonal BEKK specification can be tested by the joint exclusion of the off-diagonal elements in matrices **A** and **B** given in equation (2.7). We see in table 4.b that the null hypothesis of a diagonal BEKK specification is rejected at the 1% level, indicating that the off-diagonal elements in both matrices **A** and **B** are jointly different from zero. Analogously, volatility spillover effects in one of these three markets can be tested by the joint exclusion of the elements in the **A** and **B** matrices associated with the other two markets. Specifically, the null hypothesis for a spillover test from markets j and ℓ to market i is $a_{ji} = a_{\ell i} = b_{ji} = b_{\ell i} = 0$. Test results show that there are volatility spillovers to each of these markets from the other two.

Beyond the estimated parameters discussed above, we further consider the transformed parameters in conditional variance equations (shown in equations (A.1)-(A.3) in the appendix).[18] The transformed estimated parameters (presented in the appendix table A.4) show that the ARCH effect of CBOT soybean ($\varepsilon^2_{S,t-1}$) is statistically significant in the conditional variance equation of the DCE soybean oil, while its GARCH effect ($h_{SS,t-1}$) is statistically significant in that of soybean meal. On the other hand, the coefficients on the ARCH and GARCH terms of the DCE soybean oil ($\varepsilon^2_{O,t-1}$ and $h_{OO,t-1}$) are statistically significant in the conditional variance equation of the CBOT soybean, while only the GARCH term of the DCE soybean meal ($h_{MM,t-1}$) is statistically significant in the U.S. soybean variance. This implies a bidirectional spillover

[18] For brevity, the transformed estimation results for covariance equations are not provided; however, they are available from authors upon request.

among the U.S. soybean and the Chinese soybean oil markets in ARCH effects, while there is a bidirectional spillover between the U.S. soybean and the Chinese soybean meal futures markets in GARCH effects. Among two economic events considered, only the price spikes caused by the financial crisis significantly increased the conditional variances of the DCE soybean meal by 0.072, implying its predicted conditional variance was systematically different when the financial crisis led to a global economic slowdown from 2007 to mid-2009.

Figure 2.2 depicts predicted conditional variances for all three commodities. The figure shows that the conditional variance of DCE soybean meal spiked during the global financial crisis, which is consistent with its transformed parameter estimates significant at the 5% level (table A.4 in the appendix). A spike in the conditional variance can be also observed in figure 2.2 for both DCE soybean oil and CBOT soybean markets; however, the transformed coefficient on the financial crisis dummy is statistically insignificant in either market. An explanation for this contrasting finding could be the calculation of the transformed coefficients, which are measured by the summation of squared estimated parameters in the $\mathbf{G}_{\boldsymbol{k}}$ matrix defined in equation (2.7), such as $g_{1,SO}$ and $g_{1,SS}$. These estimated parameters are less than 0.04, thus their squared values will be further smaller and indifferent to zeros. To better observe the trend in conditional correlations between the commodity pairs, annual conditional correlations are presented in figure 2.3. The figure shows a decreasing level of volatility interdependence in each of these correlations, among which the correlation between Chinese soybean meal and oil is the lowest and most volatile.

Volatility spillovers across time

The identification of volatility spillovers could be affected when neglecting the existing structural breaks (Van Dijk, Osborn, and Sensier 2005). We examine whether the volatility spillovers across the U.S. soybean and Chinese soybean product markets have changed in different sample periods. To this end, we utilize the multivariate structural break test proposed by Qu and Perron (2007) and find a structural break in September 2009.[19] This estimated structural break is consistent with China's rapid growth in soybean imports from the U.S. in 2009, which was 21.81 MMT and increased by 41.32% compared to 2008.[20] Therefore, we exclude the period during which the structural break occurred and split our sample into two: January 24, 2006 through August 31, 2009 and October 9, 2009 through December 31, 2019.[21] The results of the MGARCH-X-BEKK model estimated for each subperiod separately are presented in tables 2.6 and 2.7.[22]

A comparison of return spillover tests across two subperiods shows a significant lagged effect of U.S. soybean returns in the conditional mean equation for Chinese soybean meal market in the post-2009 period. Before August 2009, DCE soybean meal returns are only dependent on its contemporaneous values. However, in more recent years, DCE soybean meal returns not only depend on their own past returns, but also on the second lag of CBOT soybean returns, indicating a return spillover from the U.S. market. China's tariff structure favored the import of unprocessed soybean over the import of soybean meal and oil. The domestic consumption of

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[19] This test is suitable for studying unknown structural breaks in a multivariate system and avoids inference problems when changes in variances are studied in isolation (Casini and Perron 2018; Perron, Yamamoto, and Zhou 2020). Test results are presented in the appendix table A.5.

[20] The data source for China's soybean import from the U.S. is based on UN Comtrade Database, retrieved from https://comtrade.un.org/data/.

[21] We confirm the evidence of ARCH effects in all three returns during each subperiod in the appendix table A.6.

[22] The residual diagnostics tests in table A.7 support the use of MGARCH models with multivariate Student's *t* distribution in both subperiods. Comparing to the pre-2009 period, MGARCH-X(1,1) is better fitted in the post-2009 period. Moreover, we fail to reject the null hypotheses of independence of the residual series and no ARCH effects in the residual series in both subperiods.

soybean meal has been rapidly growing since 2009 (Gale, Valdes, and Ash 2019), which further spurred Chinese soybean import from major soybean suppliers, such as the U.S. Our result on return spillover is consistent with the fact that Chinese soybean import is driven by the rapid growth of soybean meal consumption.

In the conditional variance equations, the magnitude of own-ARCH coefficient on U.S. soybean increases after 2009, while those of both Chinese soybean meal and oil decrease. These findings imply an increase in direct effects of own lagged innovations to the current conditional variances in the U.S. soybean market as opposed to Chinese soybean oil and meal markets. On the other hand, the own-GARCH coefficients are all large and statistically significant at the 1% level in both subperiods, indicating high persistence in own volatility. Moreover, there is statistical evidence of volatility spillover effects and the diagonal BEKK specification is rejected for both subperiods. Although spillover test for DCE soybean meal becomes weaker in the post-2009 period, the diagonal BEKK test for joint exclusion indicates the cross effects exist during both periods.

Moreover, we consider the impact of either the financial crisis or the retaliatory soybean tariff on the conditional variance in each subperiod. We find an increase in the conditional variance of DCE soybean meal by 0.082 and that of DCE soybean oil by 0.087 during the financial crisis, while there is no change in conditional variances of all three commodities in response to the trade dispute (table A.8 in the appendix). This finding indicates a global recession has more severe impact on price volatility than a bilateral trade conflict does. Although U.S. and China are dominant in the global soybean market, the trade conflict between two countries does not bring extra volatility in futures markets. It is because China’s demand for soybean imports is derived from livestock products and edible oil. The consumption of animal protein and edible oils has been increasing since China liberalized its foreign trade in 1990s (Gale, Valdes, and Ash 2019) and the steady growth in consumption of livestock products and soybean-based foods is expected to continuously drive the rising demand for soybeans in the next 10 years (Ministry of Agriculture and Rural Affairs, RPC 2020). While the trade conflict shifted China' soybean import from the U.S. to other soybean suppliers, it did not shrink China's consumption of soybean meal and oil (Ministry of Agriculture and Rural Affairs, RPC 2020).

Volatility impulse response functions

To better illustrate volatility spillovers, we perform impulse response analyses, which measure the behavior of a series in response to a shock hitting the series. We do so to study separately how conditional variance of each market responds to a shock originating from another market. The traditional impulse function is designed for linear models, and later it is expanded to analyze impacts of a shock on nonlinear dynamic structures (Gallant, Rossi, and Tauchen 1993; Koop, Pesaran, and Potter 1996) and conditional volatility in GARCH models (Lin 1997; Hafner and Herwartz 2006). To trace the impacts of a shock on volatility in the MGARCH-X-BEKK model, we follow Hafner and Herwartz (2006) to convert the full BEKK model to VECH form.[23]

Figures 2.4 through 2.6 show the simulated responses in the variance of each market to shocks generating from the DCE soybean meal, DCE soybean oil, and CBOT soybean market, respectively, during three periods: full sample period, pre-2009 period, and post-2009 period.

[23] To trace the impact of a shock in the full BEKK model, we rewrite equation (2.6) in VECH form as follows: $vech(\mathbf{H}_t) = \mathbf{c} + \boldsymbol{\alpha} vech(\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}') + \boldsymbol{\beta} vech(\mathbf{H}_{t-1})$, where *vech(・)* is an operator to stack the lower fraction of 3×3 matrices, $\mathbf{H}_t$ and $\mathbf{H}_{t-1}$,defined in equation (2.7) to 6-dimensional vectors. $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are 6×6 parameter matrices, while $\mathbf{c}$ is 6×1 parameter vector. We checked all eigenvalues of matrix $\boldsymbol{\alpha} + \boldsymbol{\beta}$ whether they have modulus smaller than one. This condition confirms the vector process of $\boldsymbol{\varepsilon}_t$ is covariance-stationary with its covariance matrix $\mathbf{H}_t$ in the BEKK-VECH form (Hafer and Herwartz 2006).

The shock is equivalent to a 1% increase in the conditional variance of the market where it first occurs, and the responses are calculated as percentage change from the initial conditional variance in each market.

Similar to the full-sample results, volatility spillovers from the DCE soybean meal to all three markets can be observed in both the pre-2009 and post-2009 period in figure 2.4. More specifically, the conditional variance of DCE soybean meal is instantly and severely affected by its own-volatility spillover in the pre-2009 period, and the change in variances is decreasing to zero at around 60 days, implying a short-term impact of this own shock. In addition, we observe a similar pattern for cross-volatility spillover from the DCE soybean meal to CBOT soybean during the pre-2009 and post-2009 period. The change in conditional variance of CBOT soybean starts at a positive level, slight decreasing with a bottom at 10 days, increasing to a peak around 35 days, and then slowly decreasing to zero in each subperiod. On the other hand, the conditional variance of DCE soybean oil has a delayed response to this cross-volatility spillover after 2009 and presents a longer-lasting decay in the post-2009 period than in the pre-2009.

In figure 2.5, we also observe volatility spillovers from the DCE soybean oil to both DCE soybean meal and CBOT soybean markets during three periods. Comparing with volatility spillovers before 2009, there are two important changes in the post-2009 subperiod: 1) all the spillovers have become much weaker after 2009; 2) the spillover does not immediately affect the conditional variance and takes a long time to be decayed in DCE soybean meal market. These two changes are consistent with the decreasing predicted correlations between these markets estimated from the MGARCH-X-BEKK model, further indicates a weakening impact of cross-volatility spillovers from DCE soybean oil over time.

Similarly, we observe weaker volatility spillovers from the CBOT soybean to both DCE soybean meal and oil markets after 2009 (figure 2.6). Especially in the DCE soybean meal market, the instant response to a CBOT soybean shock shrinks from 2.51% in the pre-2009 period to 0.58% in the post-2009 period. These findings are not surprising since China has been diversifying its soybean import from the U.S. to other South American countries like Brazil and Argentina. Therefore, U.S. soybean price levels and volatility are not the only source to affect the volatilities of Chinese soybean products in more recent years, regardless of a stable growth in soybean trading volume between two countries.

Conclusions

Price volatility is of great concern for farmers to manage the production and a major threat for policymakers to guarantee food security in the society. Volatility transmission along a supply chain or among horizontally related markets has been well studied. However, with the diversity of products and the development of globalization, few extensive research has been conducted to determine whether volatility transmission exists along a cross-border supply chain. Our paper contributes to this literature by examining the volatility transmission between soybean and its products that are linked in a cross-border supply chain between the U.S. and China. We further investigate the changes in spillover effects across two subperiods dictated by the structural break in trade relations between two countries.

The results of full sample provide evidence of volatility spillovers in conditional variances across the U.S. soybean and Chinese soybean product markets. A bidirectional spillover across the U.S. soybean and Chinese soybean oil market is found in the ARCH effects implying the two-way effect of lagged squared innovations in these markets. On the other hand, a bidirectional spillover across the U.S. soybean and Chinese soybean meal market found in the GARCH effects indicates the two-way dependence on volatility of the other market. The impulse response analyses show 1) an innovation originating from the DCE soybean meal market has a long-run impact on its own volatility and volatility of the DCE soybean oil returns; 2) the volatility of CBOT soybean returns is more sensitive to an innovation from the DCE soybean oil market than that from the soybean meal market in the short run.

Both spillover and diagonal BEKK tests indicate the existence of volatility spillovers to each market from the other two markets during both subperiods we considered. The impulse response analyses further confirm the presence of cross-volatility effects among three markets in each subperiod. More specifically, these spillovers have become much weaker in the post-2009 period, which are consistent to the decreasing conditional correlations in more recent years. A possible explanation for this finding is because China has been diversifying its soybean import to other South American countries. Weakening currency, lower export taxes and prices are major incentives for China to import more South American soybean, making Brazil and Argentina soybean very competitive against the U.S. soybean (USDA 2017, 2018).

Our findings for volatility reactions to two significant economic events, the 2008 global financial crisis and 2018 U.S.-China trade dispute, show that only the financial crisis significantly increased volatility of the Chinese soybean meal returns. In addition, when we break our sample period into two subperiods, we find that the financial crises also significantly affected the return volatility of DCE soybean oil in the pre-2009 period. However, none of the markets' post-2009 volatility is affected by the increased, retaliatory soybean tariff. These findings indicate a bilateral trade conflict does not spike price volatility as a global recession does. Although the 25% retaliatory tariff on the U.S. soybean led to a dramatic contraction in the value of U.S. soybean exports to China from $12.22 billion in 2017 to $3.12 billion in 2018, the average export price was $9.68 per bushel in 2018, only declining 4.30% from $10.11 in 2017.[24] This is not surprising because the U.S. shifted its soybean export to other trading partners like European Union, which reduced the impact of decreased soybean export to China caused by the trade dispute.

Overall, our paper extends the analysis for volatility transmission to products linked in a cross-border supply chain. With globalization, more countries are closely related to each other in various industries, such as agriculture, energy, and manufacturing, and participate in the different stages of the cross-border supply chain deriving from each industry. Moreover, the improvement of processing techniques encourages market participants to both trade raw products and produce value-added commodities for obtaining high profits in global markets. Thus, price and volatility transmission not only exist in a raw product across the related markets in different countries, but they can also be found between the commodity produced in a given country and its products processed in other countries. The analysis of volatility spillovers along a cross-border supply chain provides an opportunity to study the connections of price volatility in upstream and downstream markets and enhance risk management by international participants. A better understanding of volatility transmission through integrated supply chains in global markets can help to capture and forecast the effects of exogenous shocks, such as foreign policies and

[24] The annual data for U.S. soybean export prices are drawn from export elevator bids at the Louisiana Gulf reported by the USDA's Agricultural Marketing Service agency, retrieved from https://www.ams.usda.gov/market-news/custom-reports.

economic news, on the price volatility in domestic markets. It can also help to prevent the production loss of domestic farmers or processors caused by price spikes in foreign markets.

Although Brazil is the biggest competitor for the U.S. to supply China's soybean imports, our study does not account for the effects of Brazilian soybean futures in volatility transmission. The reasons are two-fold. On one hand, the surge in China's import of Brazilian soybean and the decrease import of the U.S. soybean in 2019 due to the trade conflict between the U.S. and China did not prove to be long lasting.[25] In 2020, the value of U.S. soybean exports to China reached to 10.6 billion dollars, up by 59.05% in value and 52.15% in volume from the previous year when the U.S. and China reached Phase One trade agreement. As of April 1, 2021, soybean exports to China have nearly tripled from the same period in 2019/2020 marketing year (USDA 2021). On the other hand, Li and Hayes (2017) find that U.S. soybean futures prices are leading the prices of Brazilian soybeans in the long run. Moreover, B3 S.A., the main stock exchange in Brazil, has been jointly working with the CME Group for technology services and cross-listing of futures products since 2007.[26] Previous studies on price discovery among internationally cross-listed securities find in general that home (origin) markets are dominant to foreign markets (Lieberman, Ben-Zion, Hauser 1999; Frijins, Gilbert, Tourani-Rad 2010). The soybean futures contracts traded at B3 are cross-listed mini-soybean futures and options contracts from the CME

[25] The U.S. and Brazilian soybeans have different harvest times due to being in the Northern and Southern Hemispheres. Before the U.S.-China trade dispute, there was almost no overlapping in the delivered months of imported soybeans: the import of the U.S. soybean typically peaks from November to March each year while that of Brazilian soybean peaks from May to September (Gale, Valdes, and Ash 2019). During the U.S.-China trade conflict, China expanded the importing window from Brazil in order to offset declining import from the U.S. Therefore, the market share of Brazilian soybean increased from 53.31% in 2017 to 65.11% in 2019, while that of the U.S. soybean sharply decreased from 34.39% to 19.21%. These data are obtained from the UN Comtrade Database, available at https://comtrade.un.org/data/.

[26] The introduction for the existing cooperation between the CME Group and B3 S.A. in soybean futures can be retrieved from https://www.cmegroup.com/media-room/press- releases/2020/6/22/cme_group_and_b3tojointly developnewsoybeanfuturescontractsconnec.html.

Group. Although Chinese retaliatory tariff caused a six-month divergence between Brazil and U.S. prices, anticipation that China might resume its import from the U.S. contributed to rebound in futures prices. For these reasons, our study does not account for the effects from Brazilian soybeans in volatility transmission between the U.S. and China futures markets. As the CME Group offers a new contract to reflect Brazilian export prices at the port of Santos since the third quarter of 2020, a future study could incorporate the role of Brazilian soybean in the volatility transmission across U.S. and China.

Table 2.1. Specifications of Futures Contracts

Exchange	Product	First Trading Date	Delivery Months	Price Quotation	Contract Unit
DCE	Soybean meal	12/22/2004	Jan., Mar., May, Jul., Aug., Sep., Nov., Dec.	Yuan/MT	10MT
DCE	Soybean oil	1/9/2006	Jan., Mar., May, Jul., Aug., Sep., Nov., Dec.	Yuan/MT	10MT
CBOT	Soybean	10/5/1936	Jan., Mar., May, Jul., Aug., Sep., Nov.	Cent/bushel	5,000 bushels

Notes: DCE = Dalian Commodity Exchange; CBOT = Chicago Board of Trade; MT = Metric ton; 10 MT of soybean meal = 463.9 bushels of soybeans; 10 MT of soybean oil =2060 bushels of soybeans.

Table 2.2. Summary Statistics of Returns

	Asynchronous Futures Returns						Synchronized Futures Returns			
	DCE Soybean Meal		DCE Soybean Oil		CBOT Soybean		DCE Soybean Meal		DCE Soybean Oil	
Mean	0.033		0.000		0.030		0.033		-0.001	
Std. Dev.	1.135		1.092		1.450		1.212		1.191	
Min	-5.211		-5.661		-7.411		-8.216		-8.412	
Max	5.337		4.772		6.445		6.719		5.434	
Skewness	-0.128		-0.421		-0.170		-0.159		-0.376	
Kurtosis	5.668		6.492		5.527		6.101		6.620	
Observations	3256		3256		3256		3252		3252	
ADF test	-50.822	***	-50.434	***	-57.406	***	-54.797	***	-54.480	***
Normality	974.894	***	1750.546	***	882.117	***	1316.800	***	1852.250	***
White test	93.304	***	271.653	***	141.633	***	173.648	***	315.693	***
ARCH effect	277.316	***	458.036	***	255.154	***	323.910	***	419.123	***
Ljung-Box(5)	50.510	***	61.423	***	3.254		12.789	**	14.627	**
Ljung-Box(25)	89.922	***	83.187	***	27.325		57.128	***	44.660	***

Notes: Returns are calculated as the percentage change in the settlement prices from one day to the next. DCE = Dalian Commodity Exchange; 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. White test is a heteroskedasticity test with the null hypothesis of homoskedasticity. ARCH effect is a Lagrange multiplier test for autoregressive conditional heteroskedasticity (ARCH) with the null hypothesis of no ARCH effects. Ljung-Box is an autocorrelation test with the null hypothesis of independently distributed returns. Five lags are used for the ADF, White, and ARCH effect tests; both five and twenty-five lags are used for the Ljung-Box test. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.3. Correlations of Returns

	DCE Soybean Meal	DCE Soybean Oil	CBOT Soybean
Asynchronous Returns			
Soybean Meal	1.000		
Soybean Oil	0.639	1.000	
Soybean	0.238	0.222	1.000
Synchronous Returns			
Soybean Meal	1.000		
Soybean Oil	0.570	1.000	
Soybean	0.729	0.615	1.000

Notes: The Pearson correlation coefficients are reported. DCE=Dalian Commodity Exchange; CBOT = Chicago Board of Trade.

Table 2.4. MGARCH-X-BEKK: Conditional Mean Equation Parameters

	DCE Soybean Meal (M)	DCE Soybean Oil (O)	CBOT Soybean (S)
Constant	0.021 **	-0.003	0.026
	(0.011)	(0.013)	(0.013)
$R_{M,t-1}$	0.046 ***	-0.005	-0.006
	(0.012)	(0.012)	(0.015)
$R_{M,t-2}$	-0.018	-0.028 **	-0.030 *
	(0.013)	(0.013)	(0.016)
$R_{O,t-1}$	-0.014	0.043 ***	0.023
	(0.014)	(0.015)	(0.017)
$R_{O,t-2}$	-0.007	0.025 *	0.028 *
	(0.012)	(0.015)	(0.016)
$R_{S,t-1}$	-0.010	-0.006	-0.052 ***
	(0.010)	(0.011)	(0.012)
$R_{S,t-2}$	0.037 ***	0.032 ***	0.009
	(0.012)	(0.012)	(0.015)
Spillover test (χ^2)	11.442 **	10.385 **	11.189 **
	[0.022]	[0.034]	[0.025]
Overall exogeneity test (χ^2)			33.322 ***
			[0.000]

Notes: The sample period is from January 24, 2006 to December 31, 2019. The estimated coefficients on each term in the conditional mean equations given in (2.5) are presented. Standard errors are given in parentheses and p-values are in brackets. $R_{i,t-p}$ is the continuously compounded daily return in market *i* on day *t-p*. DCE = Dalian Commodity Exchange; CBOT = Chicago Board of Trade. Subscripts M, S, and O represent DCE soybean meal, DCE soybean oil, and CBOT soybean, respectively. The spillover test from markets *j* and ℓ to market *i* is a joint exclusion test of those markets' lagged returns in the return equation of market i, $R_{i,t-p} = R_{\ell,t-p} = 0, \forall j, \ell \neq i, \forall p$. The overall exogeneity test is a joint exclusion test of all lagged returns across all equations. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.5. MGARCH-X-BEKK: Conditional Variance Equation Parameters

	DCE Soybean Meal (M)	DCE Soybean Oil (O)	CBOT Soybean (S)
c_{iM}	0.138 ***	0.136 ***	0.150 ***
	(0.014)	(0.019)	(0.036)
c_{iO}		0.093 ***	-0.091 ***
		(0.013)	(0.034)
c_{iS}			0.083 *
			(0.043)
a_{iM}	0.138 ***	-0.028	0.061 ***
	(0.019)	(0.020)	(0.019)
a_{iO}	-0.036 *	0.148 ***	0.081 ***
	(0.021)	(0.022)	(0.020)
a_{iS}	-0.039	-0.100 ***	0.158 ***
	(0.026)	(0.027)	(0.027)
b_{iM}	0.995 ***	0.014 **	-0.030 ***
	(0.006)	(0.007)	(0.008)
b_{iO}	0.003	0.984 ***	-0.026 ***
	(0.007)	(0.008)	(0.009)
b_{iS}	0.042 ***	0.066 ***	0.925 ***
	(0.011)	(0.013)	(0.013)
$g_{1,iM}$	0.136 ***	0.214 ***	-0.087
	(0.046)	(0.055)	(0.109)
$g_{1,iO}$		0.105 ***	0.009
		(0.037)	(0.093)
$g_{1,iS}$			0.036
			(0.130)
$g_{2,iM}$	-0.039	-0.043	-0.067 *
	(0.025)	(0.026)	(0.040)
$g_{2,iO}$		0.014	0.053
		(0.022)	(0.036)
$g_{2,iS}$			0.090 **
			(0.043)
Spillover test (χ^2)	18.411 ***	32.555 ***	28.866 ***
	[0.001]	[0.000]	[0.000]
Diagonal BEKK test (χ^2)			86.930 ***
			[0.000]

Notes: The sample period is from January 24, 2006 to December 31, 2019. The estimated coefficients on each term in the conditional variance equations given in (2.6) are presented. Standard errors are in parentheses and p-values are in brackets. DCE = Dalian Commodity Exchange; CBOT = Chicago Board of Trade. Subscripts $i = M, S$, and O represent DCE soybean meal, DCE soybean oil, and CBOT soybean, respectively. The spillover test from markets j and ℓ to market i is a joint exclusion test of those markets' ARCH and GARCH terms in the variance eqution of market i, $a_{ji} = a_{\ell i} = b_{ji} = b_{\ell i} = 0, \forall j, \ell \neq i$. The diagonal BEKK test is a joint exclusion test of all off-diagonal elements in matrices **A** and **B** defined in equation (2.7). The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.6. MGARCH-X-BEKK in Two Subperiods: Conditional Mean Equation Parameters

	January 2006 - August 2009			October 2009 - December 2019		
	DCE Soybean Meal (M)	DCE Soybean Oil (O)	CBOT Soybean (S)	DCE Soybean Meal (M)	DCE Soybean Oil (O)	CBOT Soybean (S)
Constant	0.072 *	0.091 **	0.096 **	0.013	-0.023	0.011
	(0.038)	(0.036)	(0.047)	(0.017)	(0.018)	(0.021)
$R_{M,t-1}$	-0.016	-0.118 ***	-0.019	0.044 *	0.023	-0.015
	(0.048)	(0.040)	(0.050)	(0.024)	(0.023)	(0.029)
$R_{M,t-2}$	0.025	0.015	0.020	-0.031	-0.031	-0.040
	(0.031)	(0.031)	(0.036)	(0.022)	(0.021)	(0.027)
$R_{O,t-1}$	0.038	0.090 **	0.096 **	-0.011	0.030	0.007
	(0.040)	(0.038)	(0.048)	(0.022)	(0.021)	(0.028)
$R_{o,t-2}$	-0.005	-0.007	0.040	-0.018	0.020	0.012
	(0.032)	(0.034)	(0.040)	(0.021)	(0.022)	(0.027)
$R_{S,t-1}$	-0.001	0.064 *	-0.093 **	-0.008	-0.026	-0.030
	(0.035)	(0.033)	(0.043)	(0.02)	(0.021)	(0.027)
$R_{S,t-2}$	-0.032	-0.019	-0.057 *	0.062 ***	0.052 ***	0.032
	(0.026)	(0.025)	(0.031)	(0.015)	(0.016)	(0.019)
Spillover test (χ^2)	2.697	11.465 **	6.628	17.923 ***	14.231 ***	2.634
	[0.610]	[0.022]	[0.157]	[0.001]	[0.007]	[0.621]
Overall exogeneity test (χ^2)			25.873 ***			26.434 ***
			[0.011]			[0.009]

Notes: The estimated coefficients on each term in the conditional mean equations given in (2.5) are presented. Standard errors are given in parentheses and p-values are in brackets. $R_{i,t-p}$ is the continuously compounded daily return in market *i* on day *t-p*. DCE = Dalian Commodity Exchange; CBOT = Chicago Board of Trade. Subscripts *M*, *S*, and *O* represent DCE soybean meal, DCE soybean oil, and CBOT soybean, respectively. The spillover test from markets *j* and ℓ to market *i* is a joint exclusion test of those markets' lagged returns in the return equation of market *i*, $R_{j,t-p} = R_{\ell,t-p} = 0, \forall j, \ell \neq i, \forall p$. The overall exogeneity test is a joint exclusion test of all lagged returns across all equations. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.7. MGARCH-X-BEKK in Two Subperiods: Conditional Variance Equation Parameters

	January 2006 - August 2009			October 2009 - December 2019		
	DCE Soybean Meal (M)	DCE Soybean Oil (O)	CBOT Soybean (S)	DCE Soybean Meal (M)	DCE Soybean Oil (O)	CBOT Soybean (S)
c_{iM}	0.463 ***	-0.002	0.157 *	0.142 ***	0.109 ***	0.204 ***
	(0.090)	(0.060)	(0.089)	(0.026)	(0.034)	(0.061)
c_{iO}		0.116 ***	0.202 ***		0.046 *	-0.158 ***
		(0.045)	(0.053)		(0.025)	(0.030)
c_{iS}			-0.000			-0.000
			(0.195)			(0.144)
a_{iM}	0.476 ***	-0.215 ***	-0.162 ***	0.136 ***	-0.040	0.076 ***
	(0.100)	(0.076)	(0.051)	(0.027)	(0.026)	(0.025)
a_{iO}	-0.042	0.181 ***	0.041	-0.019	0.093 ***	0.087 ***
	(0.064)	(0.042)	(0.038)	(0.025)	(0.024)	(0.025)
a_{iS}	0.118	-0.141 **	-0.012	-0.098 ***	-0.105 ***	0.243 ***
	(0.095)	(0.055)	(0.056)	(0.036)	(0.037)	(0.034)
b_{iM}	0.677 ***	0.230 ***	0.042	1.010 ***	0.027 **	-0.056 ***
	(0.170)	(0.061)	(0.092)	(0.013)	(0.011)	(0.017)
b_{iO}	-0.050	1.011 ***	-0.011	0.018	1.011 ***	-0.056 ***
	(0.059)	(0.023)	(0.028)	(0.013)	(0.010)	(0.017)
b_{iS}	-0.023	0.118 ***	0.935 ***	0.075 ***	0.078 ***	0.883 ***
	(0.084)	(0.041)	(0.037)	(0.019)	(0.015)	(0.023)
$g_{1,iM}$	0.228	-0.073	-0.156			
	(0.153)	(0.166)	(0.111)			
$g_{1,iO}$		0.212 **	-0.206			
		(0.092)	(0.148)			
$g_{1,iS}$			0.000			
			(0.224)			
$g_{2,iM}$				-0.092	-0.042	-0.062
				(0.088)	(0.056)	(0.213)
$g_{2,iO}$					0.018	0.152
					(0.055)	(0.302)
$g_{2,iS}$						0.201
						(0.205)
Spillover test (χ^2)	21.613 ***	16.744 ***	20.695 ***	12.737 **	30.697 ***	27.026 ***
	[0.000]	[0.002]	[0.000]	[0.013]	[0.000]	[0.000]
Diagonal BEKK test (χ^2)			61.260 ***			65.963 ***
			[0.000]			[0.000]

Notes: The estimated coefficients on each term in the conditional variance equations given in (2.6) are presented. Standard errors are in parentheses and p-values are in brackets. DCE = Dalian Commodity Exchange; CBOT = Chicago Board of Trade. Subscripts $i = M$, S, and O represent DCE soybean meal, DCE soybean oil, and CBOT soybean, respectively. The spillover test from markets j and ℓ to market i is a joint exclusion test of those markets' ARCH and GARCH terms in the variance equation of market i, $a_{ji} = a_{\ell i} = b_{ji} = b_{\ell i} = 0,\ \forall j,\ \ell \neq i$. The diagonal BEKK test is a joint exclusion test of all off-diagonal elements in matrices A and B defined in equation (2.7). The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

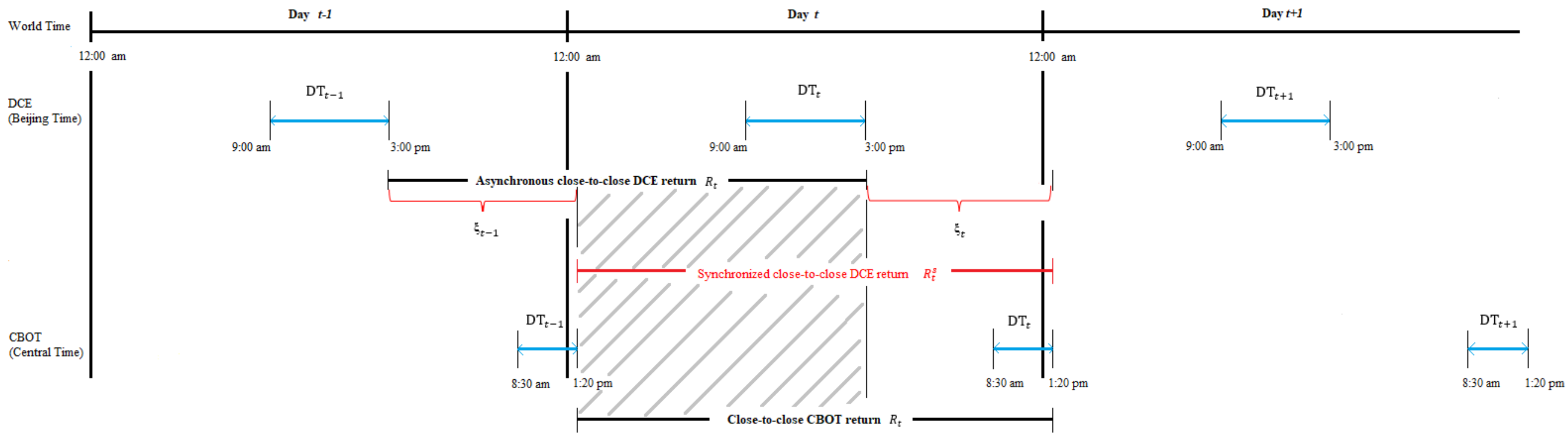

Figure 2.1. Trading hours in DCE and CBOT futures markets

Notes: World time is Greenwich Mean Time. DCE = Dalian Commodity Exchange; CBOT = Chicago Board of Trade. We calculate close-to-close returns by using settlement prices in each market. For brevity, we only plot daytime trading hours, DT. The shaded area shows the overlap of close-to-close returns between DCE and CBOT on day *t*. We use CBOT futures market as an anchor for synchronization to convert the asynchronous returns (black line) to synchronous returns (red line). The key for synchronization is to predict the unobservable component ξ_t, representing what the return would be if the market were open.

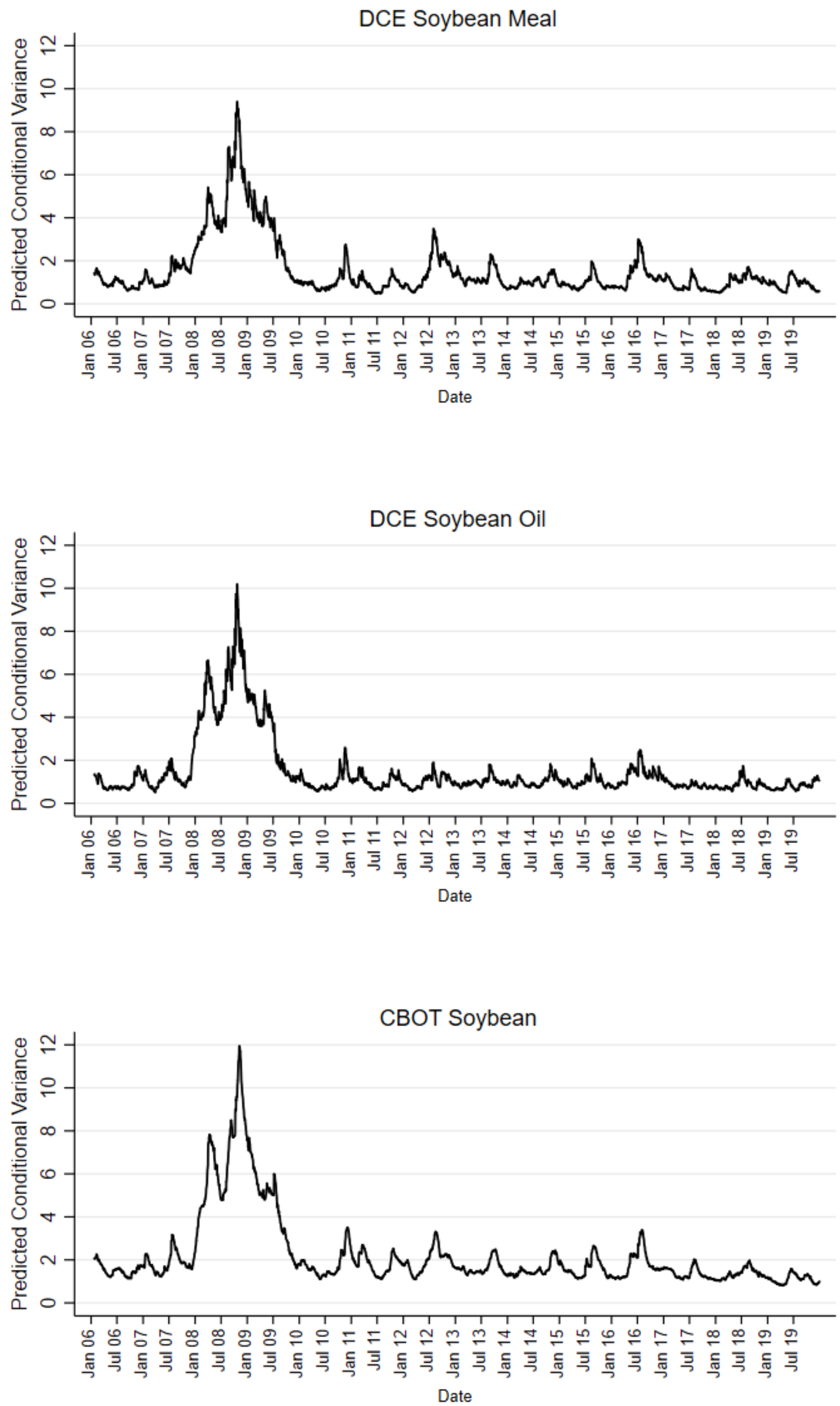

Figure 2.2. Predicted conditional variances

Notes: The conditional variances are derived from the MGARCH-X-BEKK estimation results. The sample period is January 24, 2006-December 31, 2019.

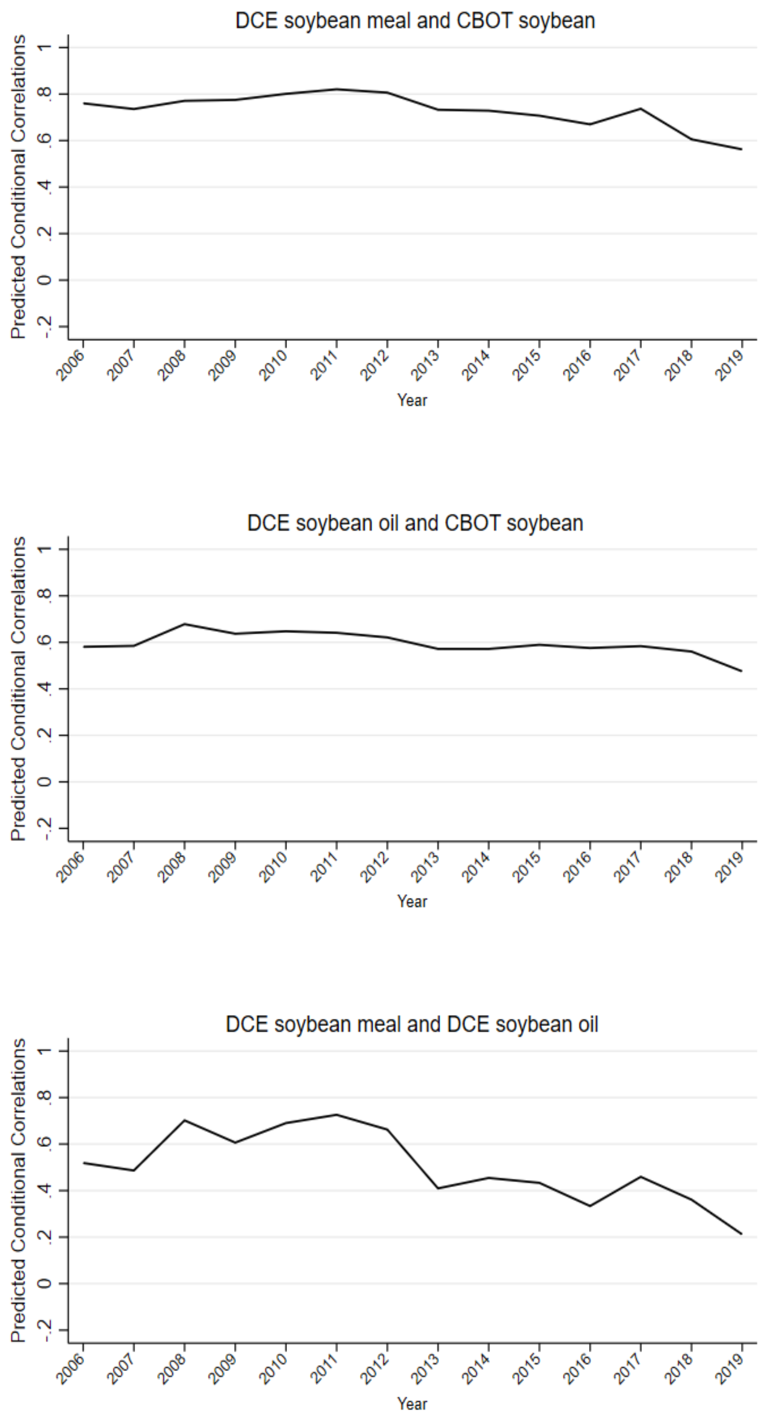

Figure 2.3. Annual average conditional correlations

Notes: Annual average correlations are derived from the daily conditional correlations estimated from the MGARCH-X-BEKK model. The sample period is January 24, 2006-December 31, 2019.

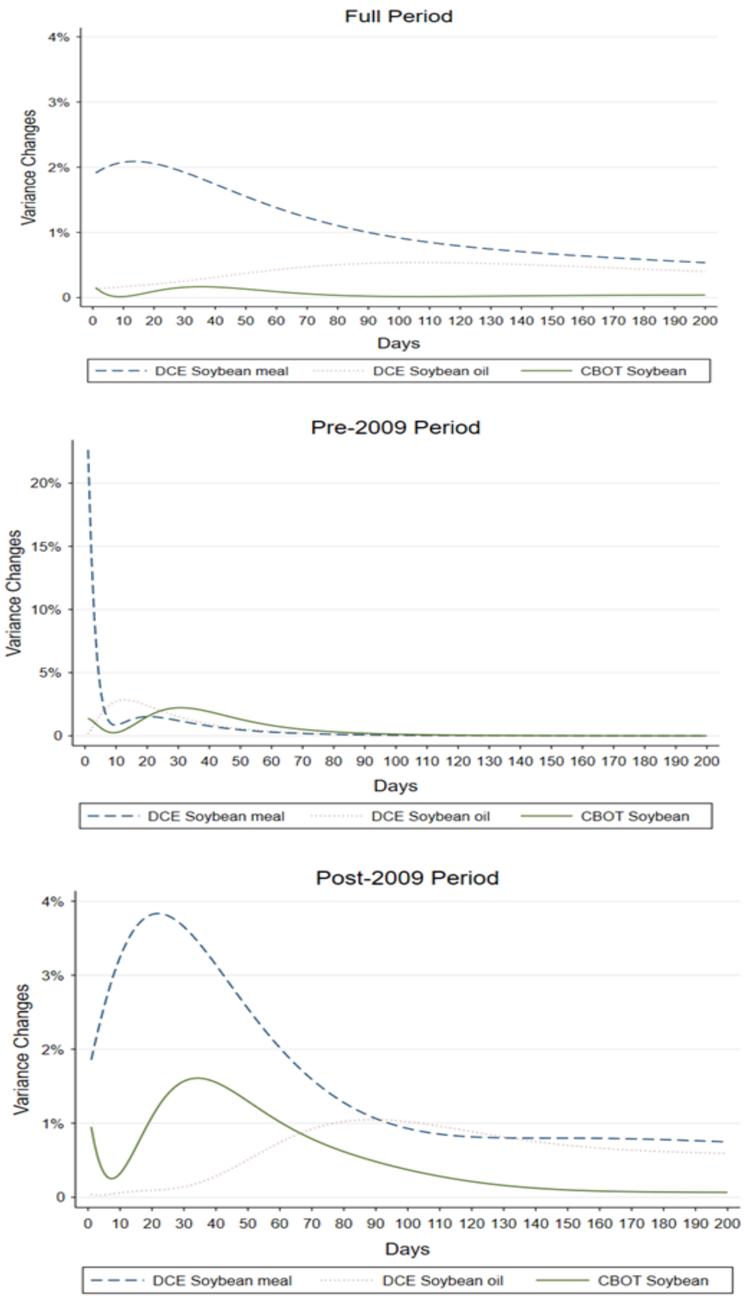

Figure 2.4. Volatility impulse response functions: DCE soybean meal shock

Notes: The impulse responses are the results of a 1% shock in the conditional variance of DCE soybean meal market where the shock first occurs. The responses are derived from the MGARCH-X-BEKK model estimation results and measured in percentages. Days on the horizontal axis refer to the time horizon following the shock. Full period corresponds to January 24, 2006-December 31, 2019, pre-2009 period to January 24, 2006-August 31, 2009, and post-2009 period to October 9, 2009-December 31, 2019.

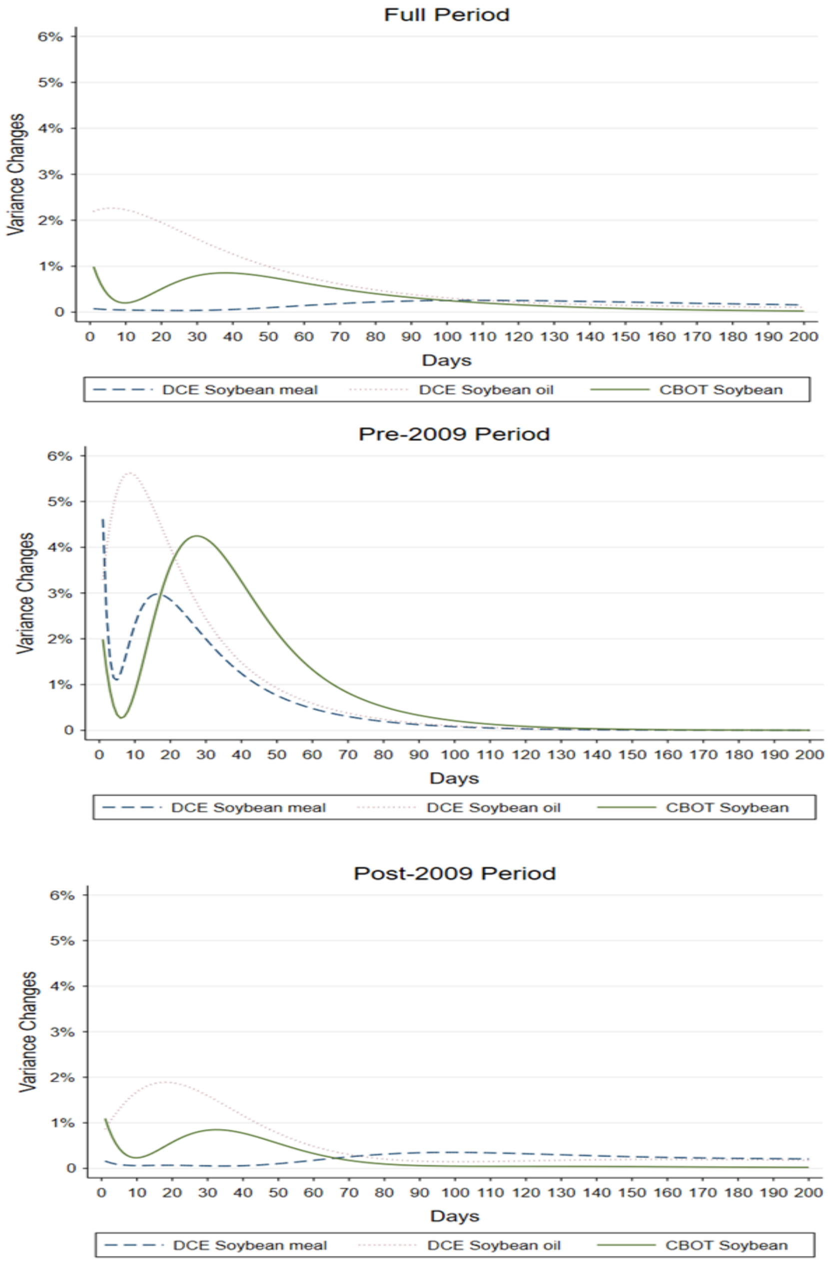

Figure 2.5. Volatility impulse response functions: DCE soybean oil shock

Notes: The impulse responses are the results of a 1% shock in the conditional variance of DCE soybean oil market where the shock first occurs. The responses are derived from the MGARCH-X-BEKK model estimation results and measured in percentages. Days on the horizontal axis refer to the time horizon following the shock. Full period corresponds to January 24, 2006-December 31, 2019, pre-2009 period to January 24, 2006-August 31, 2009, and post-2009 period to October 9, 2009-December 31, 2019.

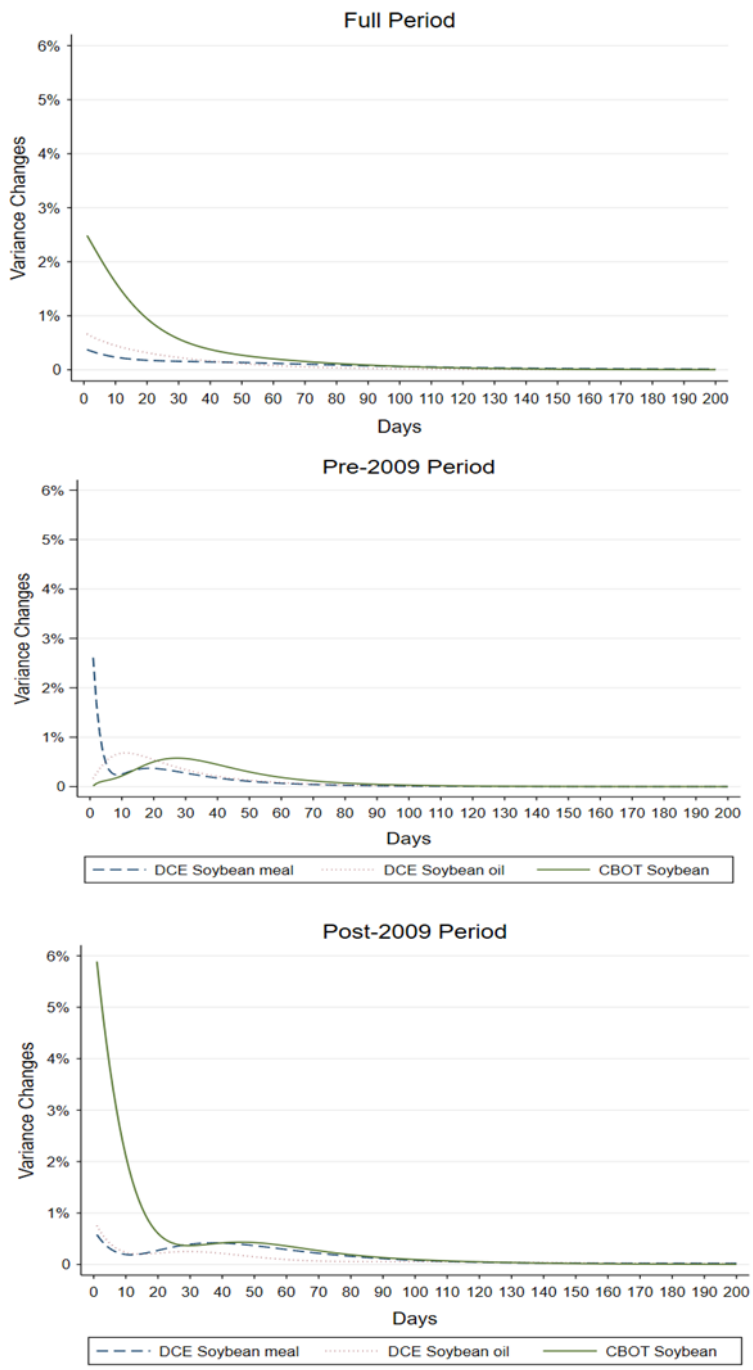

Figure 2.6. Volatility impulse response functions: CBOT soybean shock

Notes: The impulse responses are the results of a 1% shock in the conditional variance of CBOT soybean market where the shock first occurs. The responses are derived from the MGARCH-X-BEKK model estimation results and measured in percentages. Days on the horizontal axis refer to the time horizon following the shock. Full period corresponds to January 24, 2006-December 31, 2019, pre-2009 period to January 24, 2006-August 31, 2009, and post-2009 period to October 9, 2009-December 31, 2019.

CHAPTER 3

A MULTIVARIATE QUANTILE APPRROACH FOR TESTING ASYMMETRIC PRICE TRANSMISSION IN A JOINT PRODUCTION PROCESS [27]

[27] Yang Y., and B. Karali. To be submitted to *Journal of Agricultural and Resource Economics*

Abstract

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, however, has not been empirically tested in the literature for a joint production process, in which an input is transformed into more than one output, despite strong connections among the markets and the possibility that one output's price response to an input price change might depend on the other output's price level. We fill this gap by applying a vector error correction quantile (VECQ) framework to investigate if and under which market conditions such asymmetric price transmission occurs. We apply our model to two soybean end products, soybean meal and oil, that are jointly produced by crushing soybeans. We find that the prices of end products respond more to input price increases rather than decreases when their own market is bullish but the other product's market is bearish, confirming the rockets and feathers pattern at the extreme deciles of the price change distributions.

"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. 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.[28]

Previous studies, both theoretical and empirical, consider the production process for a single output.[29] But many raw materials or products can be processed into more than one output. 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

[28] 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).
[29] 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 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.

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, Gil, and Goodwin 2006).[30]

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 to depend on each other.[31] Specifically, we investigate price responses for every pair

[30] 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.

[31] 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).

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 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 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 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. 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.[32] In the case of cointegrated series, the VARQ model is misspecified and therefore a VECQ model needs to be employed.

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 $\mathbf{p}_{-\mathrm{i,t}} = (\dots, p_{i-1,t}, 0, p_{i+1,t}, \dots)'$ includes all prices excluding commodity *i* and $\Delta\mathbf{p}_{-\mathrm{i,t}} = (\dots, \Delta p_{i-1,t}, 0, \Delta p_{i+1,t}, \dots)'$ is the corresponding first differences. We use the augmented quantile

[32] 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.

regression (Xiao 2009) to investigate the cointegrating relationships at different conditional quantiles, $q_{p_{i,t}}(\tau_i|\mathbf{p}_{-\mathrm{i,t}})$, as follows:

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

where $F_{\varepsilon}^{-1}(\tau_i)$ is the inverse cumulative distribution function of the residuals for each commodity i.[33] The cointegrating relationships can be tested based on the quantile regression residual as $\varepsilon_{\tau_i,t} = p_{i,t} - q_{p_{i,t}}(\tau_i|\mathbf{p}_{-\mathrm{i,t}})$.[34]

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 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

[33] Parameters α, $\boldsymbol{\beta}'$, $\boldsymbol{\pi}_{\mathbf{j}}$ 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.
[34] In our empirical analysis, the number of leads and lags, J, is two based on the Akaike information criterion.

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).[35]

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.[36,37] 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

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[35] 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).

[36] 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).

[37] 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 $\mathbf{u}$.

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 $\Delta p^{-}_{S,t-j} = min(\Delta p_{S,t-j}, 0)$. After we identify cointegrating relationships, we denote $\mathbf{X}_{\mathrm{t}} = (\Delta \mathbf{w}'_{\mathrm{t}-1}, \mathbf{Z}'_{\mathrm{t}})'$, where $\mathbf{w}_{\mathrm{t}} = (p_{M,t}, p_{O,t})'$, $\mathbf{Z}_{\mathrm{t}} = (\widehat{EC}_{t-1}, \sum_{j=0}^{J} \Delta p^{+}_{S,t-j}, \sum_{j=0}^{J} \Delta p^{-}_{S,t-j})'$, and $\widehat{EC}_{t-1}$ are the estimated quantile cointegrating relationships defined in equation (3.1) among the price series at different multivariate quantiles $\boldsymbol{\nu} = (\tau_M, \tau_O)'$ with τ_M and τ_O representing quantile indices of soybean meal and oil, respectively. We then write the directional quantiles as follows:

(3.2) $\{\boldsymbol{\gamma}(\tau_i, \mathbf{d}, \boldsymbol{\Gamma}_{\mathrm{d}})', \boldsymbol{\theta}(\tau_i, \mathbf{d}, \boldsymbol{\Gamma}_{\mathrm{d}})', \alpha(\tau_i, \mathbf{d})\}' \equiv \operatorname{argmin} \mathrm{E}\{\rho_{\tau_i}(\mathbf{d}'\Delta \mathbf{w}_{\mathrm{t}} - \boldsymbol{\kappa}'\boldsymbol{\Gamma}_{\mathbf{d}}{}'\Delta \mathbf{w}_{\mathrm{t}} - \boldsymbol{\theta}'\mathbf{X}_{\mathrm{t}} - \alpha)\}$,

where $\mathbf{d}$ is a directional vector of any one of the soybean end products and $\boldsymbol{\Gamma}_{\boldsymbol{d}}$ 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 $\boldsymbol{\nu}$, the system of two conditional quantile functions can be written as, (3.3) $q_M(\boldsymbol{\nu}|\mathbf{X}_\mathrm{t}) = \kappa_M(\tau_M)q_O(\boldsymbol{\nu}|\mathbf{X}_\mathrm{t}) + \sum_{\ell=1}^{\mathcal{L}} \mathbf{a}_{\mathrm{M}\ell}(\tau_M)'\Delta\mathbf{w}_{\mathrm{t}-\ell} + \sum_{j=0}^{J} b_{Mj}^{+}(\tau_M)\Delta p_{S,t-j}^{+}$

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

$$q_O(\boldsymbol{\nu}|\mathbf{X}_\mathrm{t}) = \kappa_O(\tau_O)q_M(\boldsymbol{\nu}|\mathbf{X}_\mathrm{t}) + \sum_{\ell=1}^{\mathcal{L}} \mathbf{a}_{\mathrm{O}\ell}(\tau_O)'\Delta\mathbf{w}_{\mathrm{t}-\ell} + \sum_{j=0}^{J} b_{Oj}^{+}(\tau_O)\,\Delta p_{S,t-j}^{+}$$

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

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:

(3.4) $\mathbf{q}_{\Delta\mathbf{w}_t}(\boldsymbol{\nu}|\mathbf{X}_\mathrm{t}) = (q_M(\boldsymbol{\nu}|\mathbf{X}_\mathrm{t}), q_O(\boldsymbol{\nu}|\mathbf{X}_\mathrm{t}))'$,

$$\boldsymbol{\kappa}(\boldsymbol{\nu}) = (\kappa_M(\tau_M), \kappa_O(\tau_O))',\ \mathbf{a}(\boldsymbol{\nu}) = \begin{bmatrix} \mathrm{a}_{M1}(\tau_M) & \cdots & \mathrm{a}_{M\mathcal{L}}(\tau_O) \\ \mathrm{a}_{O1}(\tau_O) & \cdots & \mathrm{a}_{O\mathcal{L}}(\tau_O) \end{bmatrix},$$

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

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

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

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

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

$$(3.6)\qquad \mathbf{B}^{+}(\boldsymbol{\nu}) := \{\mathbf{I}_2 - \boldsymbol{\kappa}(\boldsymbol{\nu})\}^{-1}\mathbf{b}^{+}(\boldsymbol{\nu}) = \begin{bmatrix} B_{M0}^{+}(\boldsymbol{\nu}) & \dots & B_{MJ}^{+}(\boldsymbol{\nu}) \\ B_{O0}^{+}(\boldsymbol{\nu}) & \dots & B_{OJ}^{+}(\boldsymbol{\nu}) \end{bmatrix},$$

and the price responses to soybean price decreases are

$$(3.7)\qquad \mathbf{B}^{-}(\boldsymbol{\nu}) := \{\mathbf{I}_2 - \boldsymbol{\kappa}(\boldsymbol{\nu})\}^{-\mathbf{1}}\mathbf{b}^{-}(\boldsymbol{\nu}) = \begin{bmatrix} B_{M0}^{-}(\boldsymbol{\nu}) & \dots & B_{MJ}^{-}(\boldsymbol{\nu}) \\ B_{O0}^{-}(\boldsymbol{\nu}) & \dots & B_{OJ}^{-}(\boldsymbol{\nu}) \end{bmatrix}.$$

In addition, the adjustment speeds, $\mathbf{C}(\boldsymbol{\nu}) := \{\mathbf{I}_2 - \boldsymbol{\kappa}(\boldsymbol{\nu})\}^{-\mathbf{1}}\mathbf{c}(\boldsymbol{\nu})$, 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 $\boldsymbol{\nu}$ is

$$(3.8)\qquad \lambda_i^{+}(\boldsymbol{\nu}) = \textstyle\sum_{j=0}^{J} B_{ij}^{+}(\boldsymbol{\nu}),$$

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

$$(3.9)\qquad \lambda_i^{-}(\boldsymbol{\nu}) = \textstyle\sum_{j=0}^{J} B_{ij}^{-}(\boldsymbol{\nu}).$$

The difference between these responses, $\lambda_i = \lambda_i^{+}(\boldsymbol{\nu}) - \lambda_i^{-}(\boldsymbol{\nu})$, can be used for testing asymmetric price transmission.[38] 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

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

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.[39] 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.[40] 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 3.1(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 considered, soybean oil is the more valued product on a per pound basis (Irwin 2017). Figure 3.1(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.

Table 3.1 reports summary statistics of log prices and their first differences.[41] All log price series have platykurtic distributions with positive skewness, indicating the right sides of

[39] 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.
[40] These conversion factors are published by the U.S. Soybean Export, available at https://ussec.org/resources/conversion-table/.
[41] The first-differenced log prices also represent returns. We use returns, first-differenced log prices, and log price changes interchangeably throughout the article.

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.[42]

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 (3.1). 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 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 (3.5) to test for asymmetric output price responses.

[42] 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.

All coefficients in (3.5) vary across different quantiles of both soybean meal and oil return distributions and using multivariate quantile $\mathbf{\nu} = (\tau_M \in (0.1, \ldots, 0.9), \tau_O \in (0.1, \ldots, 0.9))'$ 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.[43] 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 table.[44] 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 3.3 and 3.4.

[43] Full results with fixed quantiles from 0.1 to 0.9 are available from the authors upon request.
[44] 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 (3.5) at each quantile from 0.1 to 0.9 in appendix tables B.1 and B.2 for soybean meal and oil, respectively.

The contemporaneous effects in VECQ are statistically significant at the 1% level for both soybean meal (table 3) and soybean oil (table 3.4) 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 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 3.3). 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 (1.299% 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%). 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). 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 first fix one of the end product's quantile at 0.1, 0.5, and 0.9 again to represent extremely low, median, and extremely high levels, respectively. Then, for each fixed quantile, we investigate the other end product's cumulative price responses varying its own quantile from 0.1 to 0.9. We present these cumulative price response patterns in figure

3.2.[45] The left panel in figure 3.2 shows the cumulative price responses to soybean price increases estimated by (3.8), and the right panel shows the cumulative responses to soybean price decreases given by (3.9). 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 5% 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 a standard vector error correction (VEC) model, which focuses on conditional means, are shown by horizontal lines.[46]

In figure 3.2(a), all soybean meal cumulative price responses are positive and statistically significant at the 5% level or lower, except for four cases when soybean price decreases: at $\tau_M = 0.9$ and $\tau_O \in (0.1, 0.2, 0.3, 0.4)$. 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 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, except for $\tau_M = 0.4$, when the soybean oil quantile is at 0.9. In addition, for a given soybean meal quantile τ_M, the meal price response is

[45] We report the estimated cumulative price responses at each quantile of both end products from 0.1 to 0.9 in appendix tables B.3 and B.4 for soybean meal and oil, respectively.
[46] The corresponding methods, tests, and their results for a standard VEC model are available from the authors upon request.

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 3.2(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 are all positive and 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 0.44%.

Figure 3.3 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 5% 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 3.3(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 3.3(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.

Policy Implications of Asymmetric Price Transmission

The policy concern behind a positive price asymmetry is that consumers cannot fully benefit from falling farm prices (McCorriston, Morgan, and Rayner 2001). It is easy to understand this concern for food products. Money spent on food items constitutes a large share of household expenses, especially for low-income families. According to the U.S. Department of Agriculture, households in the lowest income quantile spent about 30.6% of their income on food in 2021, whereas households in the highest income quantile spent 7.6% of their income on food (USDA 2022).

A number of theoretical studies on agricultural markets (e.g., McCorriston, Morgan, and Rayner 2001; Weldegebriel 2004; Antonova 2013) suggest market power leads to asymmetric price transmission, but none predicts a specific pattern of price asymmetry as an optimal pricing strategy in non-competitive markets (Meyer and von Cramon-Taubadel 2004; von Cramon-Taubadel and Goodwin 2021).[47] While agricultural markets have been often assumed to be competitive, the structure of the U.S. agricultural and marketing systems has been changing because of higher product quality, better product differentiation, and increasing vertical coordination and control (Sexton 2013; Sexton and Xia 2018). Growing evidence suggests that these systems in developed countries are more appropriately characterized as oligopolistic rather than competitive (e.g., Sexton 2000, 2013; McCorriston 2002). For example, the soybean crushing industry, the market we chose as our application for a joint production process, has become highly concentrated in the U.S. over the years, with four large processors (ADM,

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[47] Besides market power, price asymmetry has been also explained by adjustment costs (e.g., Barro 1972; Bailey and Brorsen 1989; Buckle and Carlson 2000), search costs (e.g., Tappata 2009; Richards, Gómez, and Lee 2014), government intervention (e.g., Kinnucan and Forker 1987), and inventory or stock management (e.g., Blinder 1982).

Cargill, Bunge, and Ag Processing) accounting for 74.5% of total sales in 2017 (U.S. Census Bureau 2017).[48]

The dependence of an end product's price response on the price level of the other end product might be more pronounced in non-competitive markets as oligopolistic firms are flexible in their pricing and production. In fact, both rockets and feathers pattern (i.e., positive price asymmetry) and the opposite pattern (i.e., negative price asymmetry) can emerge as their pricing strategy. For example, in a bullish market, where producers are experiencing high demand for their products or services, firms can thoroughly pass through an increase in production costs to consumers while not lowering their output prices in response to decreasing input costs to keep their profit margin high (Meyer and von Cramon-Taubadel 2004). In a bearish market, oligopolistic firms might have two different strategies. They can still pass through higher costs more fully than lower costs since consumers have a small number of alternative producers in the short run. Or, they can respond more fully to decreasing production costs to lower output prices in order to squeeze out the weaker rivals and seize a higher share of the market (von Cramon-Taubadel and Goodwin 2021). Therefore, price asymmetry might occur at specific, but not all, parts of the price distributions, which can be revealed with our multivariate quantile estimation approach. Our study does not formally test the existence or exertion of market power, or formally link the price asymmetry to market power, but rather it provides a new perspective for the analysis of price asymmetry in joint production that takes into account the dependence of output responses on each other.

[48] Even though 40 firms entered the soybean crushing industry from 2002 to 2017, the market share of the top four largest firms decreased only by 5.4 percentage points from 79.9% to 74.5% (U.S. Census Bureau 2002, 2017).

It should be noted that the occurrence of price asymmetry is not guaranteed in non-competitive markets. For instance, Weldegebriel (2004) points out “oligopoly and oligopsony power do not necessarily lead to imperfect price transmission, although they can.” Deconinck (2021) shows that even in the presence of market power, changes in farmgate prices can be fully transmitted to supermarkets with cost-plus contracts between processors and retailers.[49] Therefore, it is important for policymakers to explore and understand the overall functioning of a supply chain before implementing policies to balance market power with the welfare of participants at various stages of the food chain (i.e., farmers, processors, and retailers).

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. This is especially important in non-competitive markets as firms with market power are more flexible in their pricing and production decisions. 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

[49] A cost-plus contract is defined in the Federal Acquisition Regulation as “a cost-reimbursement contract that provides for payment to the contractor of a negotiated fee that is fixed at the inception of the contract.”

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.

Table 3.1. Summary Statistics of Prices and Their First Differences in the Soybean Complex

	$p_{i,t} = ln(P_{i.t})$			$\Delta p_{i,t} = ln\left(P_{i,t}\right) - ln(P_{i,t-1})$		
	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 3.2. 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 (3.1) 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.

Table 3.3. VECQ Results for Soybean Meal Responses

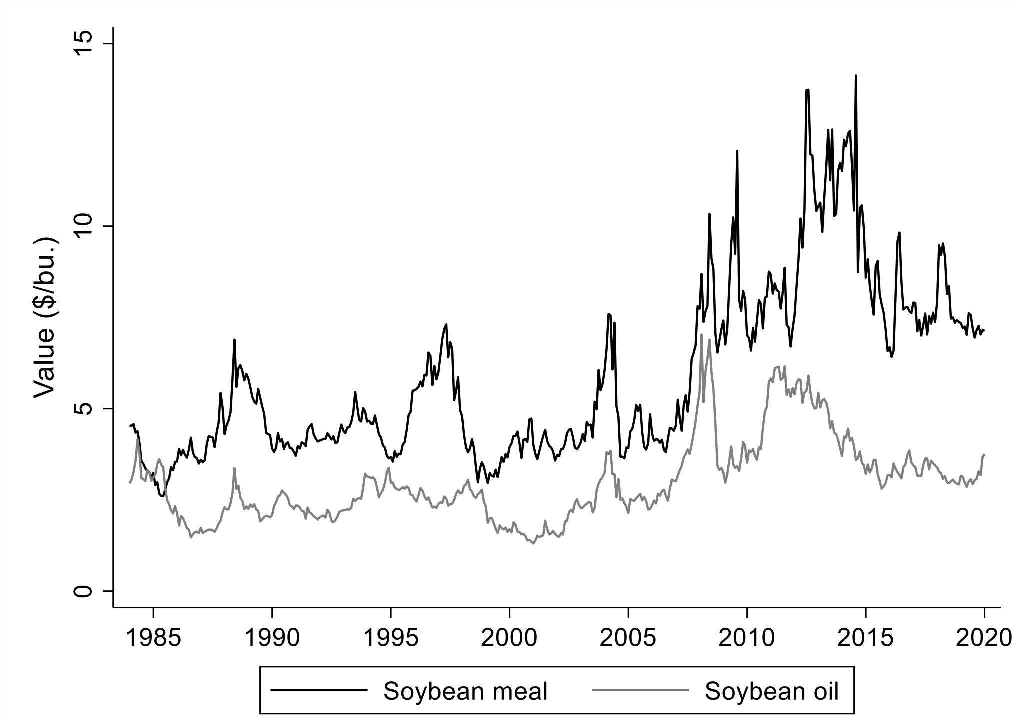
	τ_M		
	0.1	0.5	0.9
$\Delta p^+_{S,t}$	0.918***	0.952***	1.130***
	(0.199)	(0.098)	(0.205)
$\Delta p^-_{S,t}$	1.063***	0.949***	0.843***
	(0.147)	(0.074)	(0.163)
$\Delta p^+_{S,t-1}$	0.381	0.333*	0.109
	(0.267)	(0.196)	(0.264)
$\Delta p^-_{S,t-1}$	0.673***	0.379**	-0.313
	(0.198)	(0.180)	(0.253)
Cumulative price response:			
λ^+_M	1.299***	1.285***	1.240***
	(0.285)	(0.221)	(0.332)
λ^-_M	1.736***	1.328***	0.530*
	(0.259)	(0.178)	(0.297)
λ_M	-0.436	-0.043	0.710**
	[0.120]	[0.831]	[0.065]

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 $\lambda_M = 0$. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

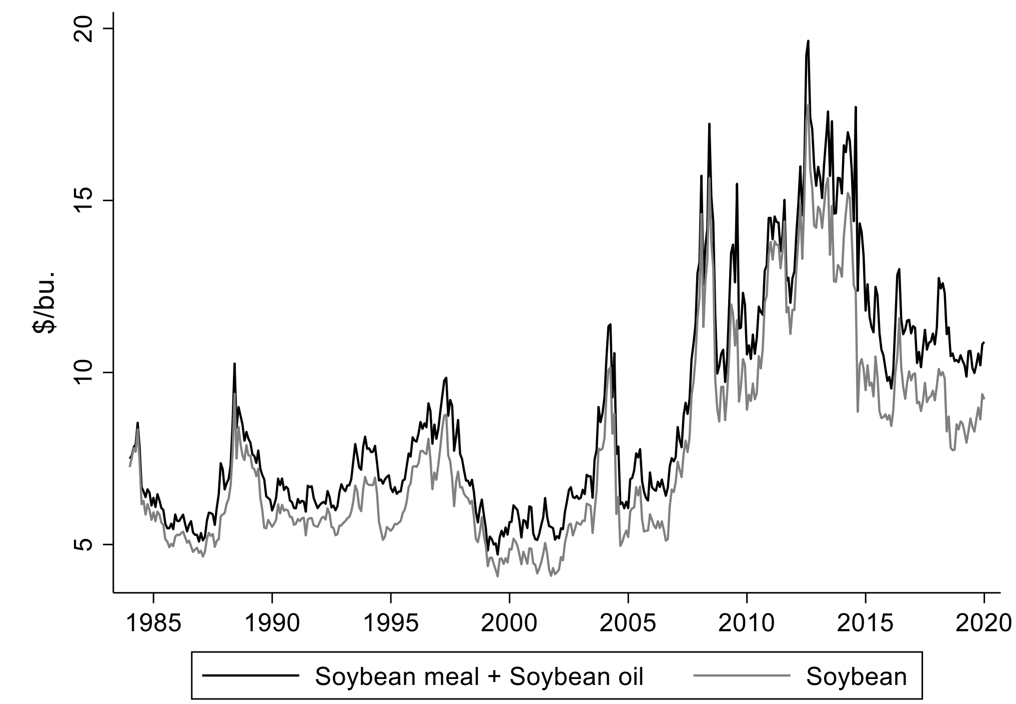
Table 3.4. VECQ Results for Soybean Oil Responses

	τ_O		
	0.1	0.5	0.9
$\Delta p^{+}_{S,t}$	0.756***	0.996***	1.029***
	(0.182)	(0.146)	(0.158)
$\Delta p^{-}_{S,t}$	0.833***	0.556***	0.311
	(0.127)	(0.097)	(0.197)
$\Delta p^{+}_{S,t-1}$	-0.058	-0.345	-0.623**
	(0.298)	(0.231)	(0.286)
$\Delta p^{-}_{S,t-1}$	0.098	-0.320	-0.746***
	(0.380)	(0.190)	(0.261)
Cumulative price response:			
λ^{+}_{M}	0.698**	0.651***	0.406
	(0.334)	(0.245)	(0.342)
λ^{-}_{M}	0.931**	0.236	-0.434
	(0.389)	(0.205)	(0.316)
λ_{M}	-0.233	0.415*	0.841*
	[0.512]	[0.088]	[0.055]

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 $\lambda_O = 0$. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

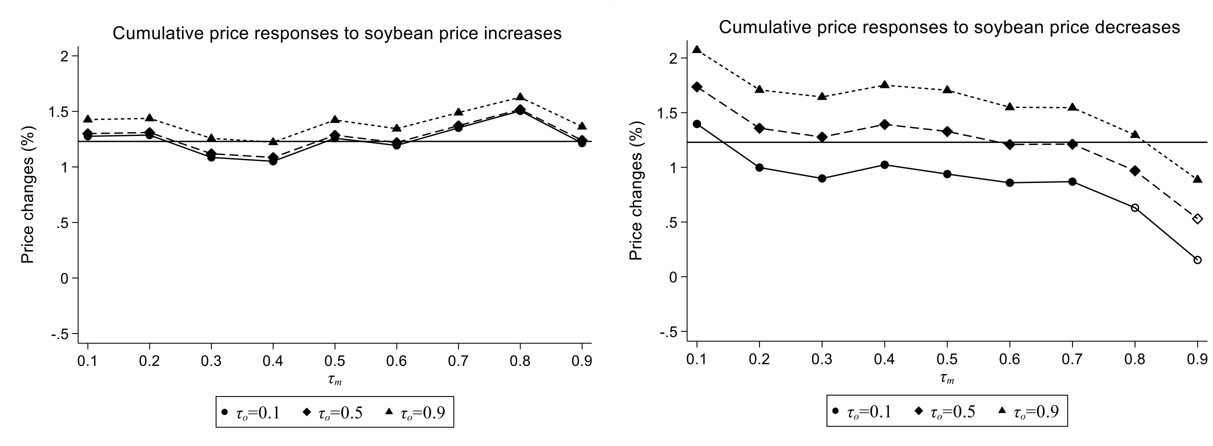


(a) Crush value of soybean meal and oil

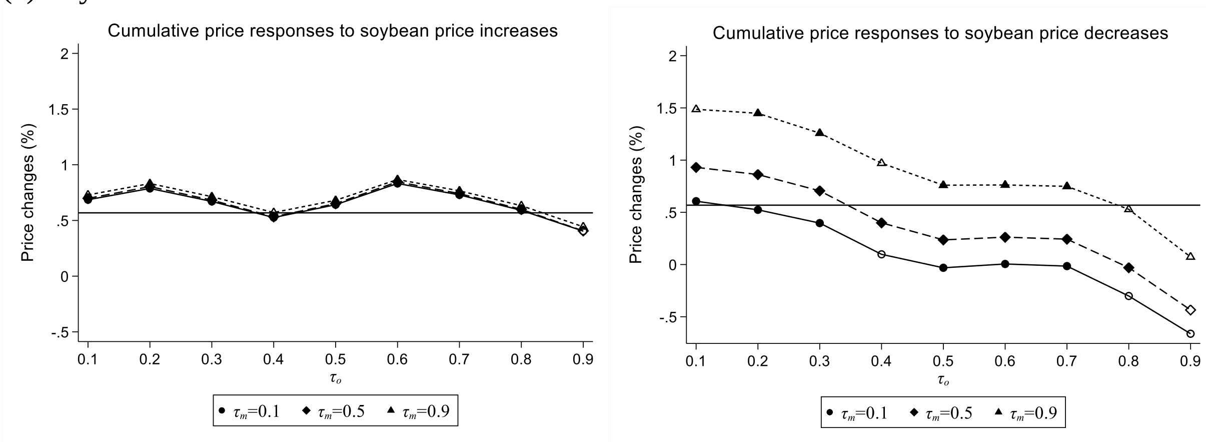


(b) Soybean prices and combined crush value of soybean meal and oil

Figure 3.1. Prices of the soybean complex



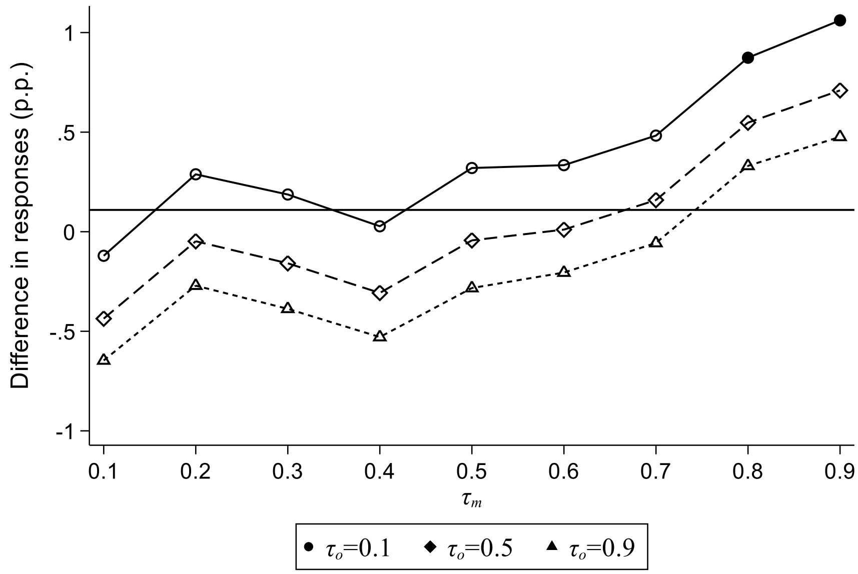
(a) Soybean meal



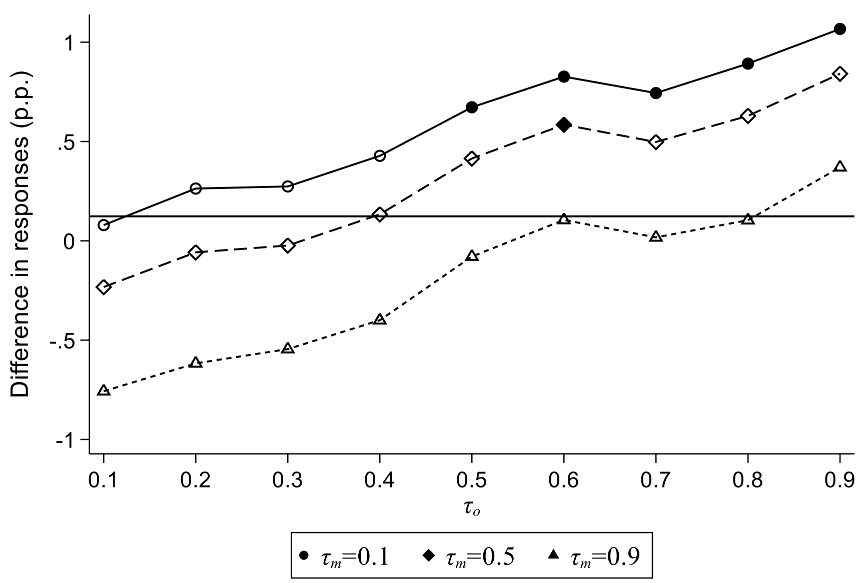
(b) Soybean oil

Figure 3.2. Output price responses to soybean price changes

Notes: Cumulative price responses to soybean price increases and decreases are calculated as in equations (3.8) and (3.9), respectively. Coefficient estimates that are statistically significant at the 5% level or lower 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.



(a) Soybean meal



(b) Soybean oil

Figure 3.3. Cumulative output price asymmetry in response to soybean price changes

Notes: Cumulative price asymmetry is calculated as the difference between responses to positive and negative price changes. Positive (negative) values indicate the response to higher (lower) soybean prices is larger than the response to lower (higher) soybean prices. Estimates that are statistically significant at the 5% or lower 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.

CHAPTER 4

THE ROLE OF USDA REPORTS ON EXTREME PRICE AND VOLATILITY MOVEMENTS IN AGRICULTURAL COMMODITIES[50]

[50] Yang, Y., and B. Karali. To be submitted to *American Journal of Agricultural Economics*

Abstract

This paper investigates the impact of USDA reports on extreme price movements in three groups of agricultural substitutes: corn-soybean, winter-spring wheat, and lean hog-live cattle-feeder cattle. We use an ordered logistic model to investigate whether the release of USDA reports has explanatory power for these coexceedances (i.e., more than one market simultaneously suffers from extreme events). After controlling for the exposure to other risk factors, our results show evidence of an increased probability of coexceedances following the release of USDA reports. Our findings find statistical evidence of an increased return and volatility coexceedances on the release days of USDA reports. More specifically, the June cluster of Acreage (ACR) and Grain Stocks (GS) has the most significant impact on increasing the occurrence of return or volatility coexceedances in grain markets, indicating that these two reports have substantial informational value. Although most report clusters have a dual effect, either increasing the probability for portfolio traders to earn or lose money on release days, some of them only impact the occurrence of low returns associated with high volatility. Our study contributes to the informational value of USDA reports on agricultural substitutes and sheds lights on trading strategies for portfolio traders who simultaneously hold multiple futures contracts.

Introduction

Extreme price movements, characterized by significant positive and negative returns, pose a substantial risk to traders in financial markets. These movements can lead to rapid collapses or rebounds in market indices, resulting in substantial financial losses. For instance, the 2010 flash crash witnessed a sharp and sudden decline in U.S. equity indices, causing nearly one trillion dollars in losses. The Commodity Futures Trading Commission (CFTC 2018) conducted an analysis of 2.2 billion transactions across 16 active futures contracts in major markets and pointed out “news and market data releases are large drivers of sharp price movements in many contracts studied.”

In agricultural markets, one prominent source of news and market data releases is the U.S. Department of Agriculture (USDA). The USDA reports provide comprehensive information on various aspects of the agricultural sector, including supply and demand categories, plantings intentions, acreage statistics, and inventories of major crops and livestock. These reports have served as a primary source of public information in the agricultural sector for many decades. Extensive literature indicates that market participants closely monitor these reports, as they have been found to have a significant impact on price movements and volatility in agricultural markets (e.g., Summer and Mueller 1989; Dorfman and Karali 2015; Adjemian and Irwin 2018; Fernandez-Perez et al. 2019; Karali, Irwin, and Isengildina-Massa 2020).

However, the economic value of USDA reports has faced challenges due to factors such as the proliferation of private information services, structural changes in market dynamics, and pressures related to federal budgetary constraints. Despite these challenges, recent studies have reaffirmed the continued influence of USDA reports on market prices and volatility (e.g., Ying, Chen, and Dorfman 2019; Karali et al. 2019; Karali, Isengildina-Massa, and Irwin 2019;

Isengildina-Massa et al. 2021). The impact of these reports on market dynamics highlights the significance of information dissemination and its role in shaping market outcomes.

Most previous studies provide evidence of the significant impacts of USDA report releases on individual agricultural commodity markets. However, USDA reports often contain information for various commodities in the same report, particularly for major crops. Ai, Chatrath, and Song (2006) find that supply factors such as planted acreage and yield per acre play a significant role in price comovements in corn, soybean, and wheat markets. The release of new commodity information through USDA reports can stimulate price comovements of multiple commodities. These price movements are essential for portfolio traders, an individual or entity that manage a combination of various futures contracts, to trade off the return and risks and maximize their profit in the portfolio. For example, spreading, a trading strategy in which traders simultaneously buy one futures contract and sell another, is commonly used to mitigate price risks associated with outright futures contracts.[51] The soybean-corn spread is a popular tool for trading the relationship between corn and soybean futures prices. Similarly, the wheat spread relies on the dynamic intermarket relationships in spring and winter wheat futures prices for different protein levels in hard red wheat. Therefore, to determine whether USDA report releases lead to market responses resembling a flash crash and undermine the hedging effectiveness of portfolio strategies, it is crucial to consider simultaneous price movements in commodities that are substitutes in consumption and/or production.

Our study makes several contributes to the existing literature on the effects of USDA reports. We take into account the clustering of report releases that occur concurrently, examine

[51] CME group defines the term *outright* as a single purchase or sale of an underlying asset for delivery at a single future date. Spreads have three categories: calendar spreads (or intramarket spreads), intermarket spreads, and commodity product spreads.

simultaneous price and volatility movements in substitute agricultural commodities, and measure the increased likelihood of extreme price and volatility movements around report releases.

To analyze these dynamics, we adopt the "coexceedance" approach developed by Bae, Karolyi, and Stulz (2003).[52] This approach allows us to identify instances of simultaneous extreme price and volatility changes around USDA report releases in three commodity pairs linked through substitution and production processes: corn-soybean, winter wheat-spring wheat, and lean hogs-live cattle-feeder cattle. Unlike previous studies that use a conditional covariance framework (e.g., Karali 2012), which treats all observations equally, our coexceedance framework focuses on the counts of coexceedances, capturing the number of markets experiencing large positive or negative movements simultaneously. We then employ an ordered logistic regression using these count measures to assess whether USDA report releases increase the probability of coexceedance occurrences.

Our study reveals an elevated probability of return and volatility coexceedances on days when USDA reports are released. Compared to livestock markets, the impact of USDA report clusters is more pronounced in grain markets. The effects of USDA reports on return coexceedances vary depending on factors such as the number of exceedances, the commodity pair, and the tail behaviors (i.e., upper or lower tail). Notably, the June cluster of Acreage (ACR) and Grain Stocks (GS) has the most significant impact on increasing the occurrence of

[52] The coexceedance method has been applied in the literature for financial contagion and integration (e.g., Baur and Schulze 2005; Christiansen and Ranaldo 2009), extreme price changes in energy futures markets (Koch 2014) and agricultural commodities (Algieri, Kalkuhl, and Koch 2017). Algieri and Leccadito (2021) develop an alternative method, an integer-valued GARCH model, to capture the temporal dependence and persistence in the coexceedances in various futures markets.

volatility coexceedances in grain markets. This indicates that these two reports have substantial informational value.

On the other hand, sufficient volatility can generate short-run arbitrage opportunities within a portfolio (Fernholz, Karatzas, and Rup 2018). Traders can use portfolios on the release days of these reports to increase their chances of benefiting from positive price movements (i.e., high returns). Our findings demonstrate that most report clusters have a dual effect, either increasing the probability for portfolio traders to earn or lose money on release days. However, the September release of GS reports and the March cluster of Prospective Planting (PP) and GS reports only impact the occurrence of low returns associated with high volatility for the corn-soybean and winter wheat-spring wheat pairs, respectively. Corn-soybean traders should avoid holding two contracts together on the release days of the GS report in September, while winter-spring wheat traders should avoid doing so on the release days of PP and GS reports. This is because traders cannot profit or diversify risks effectively with these specific portfolios on the release days of these two clusters. These findings contribute to identifying the impacts of major USDA reports on the extreme price movements in futures markets and shed light on the value of USDA information for portfolio traders engaged in simultaneous transactions of multiple commodity contracts in futures markets.

Econometric Methods

Coexceedance counts

We define daily returns as

(4.1) $$r_{it} = \left(\ln(p_{it}) - \ln\left(p_{i,t-1}\right)\right) \times 100,$$

where p_{it} is the price of commodity *i* on day *t*, and the absolute returns as $|r_{i,t}|$ to represent volatility. To identify an extreme return or volatility for each commodity, we define an exceedance as an observation that lies either below the 5% or above the 95% quantile of its distribution.

Large positive or negative price movements provide valuable information about market sentiment and trading opportunities. For example, a sudden and large price increase might indicate a positive shock from good news or increased demand, while extreme negative price movement might signal market downturns prompting investors to reassess their holdings. Therefore, we consider return coexceedances in both upper and lower tails. The exceedance count in the upper tail (i.e., the occurrence of extremely positive returns) is calculated as

(4.2) $UR_t^J = \sum_{i=1}^{N} I(r_{it} \geq QR_i^{0.95})$,

and the number of coexceedance in the lower tail (i.e., the occurrence of extremely negative returns) as

(4.3) $LR_t^J = \sum_{i=1}^{N} I(r_{it} \leq QR_i^{0.05})$,

where *N* is the number of commodities in commodity pair *J* and $I(\cdot)$ is an indicator function that equals one if the condition in parenthesis is satisfied and zero otherwise. We use the 0.95 and 0.05 quantiles of commodity *i*'s return distribution, $QR_i^{0.95}$ and $QR_i^{0.05}$, to represent the thresholds for extremely high and low returns.

As the extant literature shows that volatility increases on report release days, we only focus on the occurrence of volatility coexceedances in the upper tail. The volatility exceedance count in the upper tail (i.e., the occurrence of extremely large volatility) is calculated as

(4.4) $\quad UV_t^J = \sum_{i=1}^{N} I(|r_{it}| \geq QV_i^{0.95})$.

Determinants of coexceedances

We follow Koch (2014) and Algieri, Kalkuhl, and Koch (2017) and use a logistic regression model to explore factors that affect the probability of coexceedance occurrences. All of our exceedance counts have a natural ordering since they indicate the number of markets that experience extreme price or volatility movements. Accordingly, for each commodity pair, we employ an ordered logit model to estimate the probability of coexceedance occurrences in both tails for returns and in the upper tail for volatility. The probability of observing outcome *h* coexceedance in the ordinal model is,

(4.5) $\quad \Pr\left[W_t^J = h\right] = \Pr[\alpha_{h-1} < X'\beta + u \leq \alpha_h]$

$$= \frac{1}{1 + \exp\left(-\alpha_h + X'\beta\right)} - \frac{1}{1 + \exp(-\alpha_{h-1} + X'\beta)}$$

where $W_t^J \in \left\{UR_t^J,\ LR_t^J,\ UV_t^J\ \right\}$ and *h* represents the number of exceedances in each pair: $h = 0,\ 1,\ 2$ for the pairs including two commodities, and $h = 0,\ 1,\ 2,\ 3$ for the pairs including three commodities. The matrix X contains explanatory variables, β is the parameter vector, and α_h is the cutpoint with $\alpha_0 < \alpha_1 < \alpha_2 < \alpha_3$. Specifically, the coefficients of the ordered logistic regression, *β*, indicate changes in the log-odds of being in a higher category of the outcome *h* associated with a one-unit change in the explanatory variable, while holding other variables constant. For a straightforward interpretation, instead of the estimated coefficients, we calculate and report average marginal effects (AMEs) given by

(4.6) $\quad AME_{x_k}(h) = \frac{1}{J} \sum_{j=1}^{J} [\widehat{Pr}_j(X_k = 1|h, X_{-k}) - \widehat{\Pr}_j(X_k = 0|h, X_{-k})]$, where x_k is the k^{th} explanatory dummy variable, X_{-k} is the vector of explanatory variables excluding x_k. J is the number of total observations in each commodity pair. $\widehat{\Pr}_j(\cdot \mid h, X_{-k})$ represents the predicted probability of being in outcome h for the j^{th} observation given the other explanatory variables X_{-k}.

Data

Commodity returns and volatility

We conduct our analysis for three substitute commodity pairs: corn-soybean, winter wheat-spring wheat, and hogs-cattle-feeder cattle. In the U.S., corn and soybean are close substitutes in production and compete for acreage (Goswami and Karali 2022). Therefore, any news related to one of the crops most likely affects the other crop as well. For example, production surprises in the corn market moves soybean futures prices (Karali et al. 2019). Hard red winter wheat and hard red spring wheat are economic substitutes for milling purposes based on their substitution elasticities (Marsh 2005). Hogs and cattle are substitute protein sources and changes in consumer preferences, supply shortages, or news related to one of them would affect the other market. Feeder cattle is a young, growing cattle raised on feedlots before it is sold to meat processors; thus, it is linked to mature cattle through biological process.

We use the prices of futures contracts of these commodities from May 1, 1994 to December 31, 2022 obtained from Barchart (formerly Commodity Research Bureau).[53] Hard red spring wheat futures contracts are traded at the Minneapolis Grain Exchange, while corn, soybean, and hard red winter wheat futures at the Chicago Board of Trade (CBOT). Livestock

[53] Before May 1994, USDA announces crop production, grain stocks, other significant fundamental information with 2:00pm CT release time after futures market close. We choose the sample period to capture the announcement effect of USDA reports on the same-day trading.

futures are traded at the Chicago Mercantile Exchange (CME). After excluding weekends and holidays, our sample includes 7,222 observations for crops and 7,218 observations for livestock. We create the nearby price series by rolling over nearby contracts when the trading volume of the next nearest contract exceeds the current one.

Table 4.1 reports summary statistics of daily returns and absolute returns. Both returns and absolute returns have leptokurtic distributions with positive kurtosis, indicating that they are heavy-tailed compared to the normal distribution and have a greater chance of extreme events (either positive or negative values). In addition, the skewness of return distributions implies the direction of extremes. The return series of four commodities (corn, soybean, spring wheat, and live cattle) are negatively skewed, implying that most observations are to the right of the mean and extreme values are to the further left. The remaining three (winter wheat, lean hogs, and feeder cattle) exhibit positive skewness with a longer right tail. Of these seven commodities, soybean is the most heavily left-skewed, while lean hog has the most highly right-skewed-distribution. Moreover, the distribution is highly asymmetric when the skewness of the distribution is greater than 1 or smaller than -1. The skewness for all absolute returns is greater than 1, indicating a substantial departure from symmetry in the distribution of absolute returns.

USDA reports and clustering

We select ten USDA reports that have been extensively studied in the literature to determine the value and market-moving effect of public information. Table 4.2 describes these selected reports in detail. Majority of the crop reports are released together, known as report clustering. This makes it difficult to differentiate the impacts of multiple reports released on the same day from each other, especially when one does not take into account the report content and the associated market expectations. Therefore, we follow the suggestion of Isengildina-Massa et al. (2021) and evaluate the impact of reports on returns and volatility by focusing on the releases of the reports as a cluster. As shown in table 4.3, there are six report clusters for both crop pairs. Crop Production Annual Summary (CPAS) reports are released in January, overlapping with the January release of WASDE and Grain Stocks (GS). For the winter wheat-spring wheat pair, this cluster also contains Winter Wheat Seedings (WWS), which provides producer planting intentions for winter wheat. The other two annual reports providing information for all selected crops are Prospective Plantings (PP) in March and Acreage (ACR) in June. They are both simultaneously released with GS reports. Monthly WASDE reports summarize supply-use balances of major crops from all available sources. During the growth cycle of each crop, they contain the production data, such as area harvested and yield per acre, from the simultaneously-released Crop Production (CP). The growth cycle of corn and soybean is from August to November, from May to August for winter wheat, and from July to August for spring wheat (Isengildina-Massa et al. 2021). We separate WASDE reports that coincide with the CP reports from the other monthly WASDE releases. For the wheat pair, September release of GS overlaps with Small Grains Annual Summary (SGAS) reports. There is no clustering for livestock reports. In our empirical analysis, we use dummy variables indicating the release of these reports and report clusters.

Other determinants of coexceedances

Based on the existing literature (Tang and Xiong 2012; Tadesse et al. 2014; Koch 2014; Algieri, Kalkuh, Koch 2017; Algieri and Leccadito 2021), we choose other explanatory variables to control for the exposure of agricultural futures to common risk factors. Chicago Board of

Exchange volatility index (VIX) and S&P 500 index (SP500) are obtained from Barchart. To represent market volatility and sentiment, we include daily news-based economic uncertainty index (News), and policy-related economic uncertainty index (EPU), created by Baker, Bloom, and Davis (2016).[54] A stronger U.S. dollar makes the U.S. exports relatively more expensive and reduce the demand for agricultural products from other countries. We include the daily U.S. dollar exchange rate relative to a basket of its trade partners' currencies (DXY), obtained from Barchart. As agricultural commodity prices are sensitive to inflationary pressures, we include both Consumer Price Index (CPI) and Producer Price Index (PPI) as control variables, both attained from the Economic Research Division of the Federal Reserve Bank of St. Louis.[55] To capture the impact of shocks in these other factors on return and volatility coexceedances, we create dummy variables accounting for large shocks (i.e., daily changes, or returns, above the 0.95 quantile of their distributions) and small shocks (i.e., daily changes, or returns, below the 0.05 quantile).[56]

Empirical Results

Coexceedance counts in the entire sample

We report the frequency and percentage of return and volatility coexceedances in table 4.4 for our entire sample period. An exceedance of return or volatility is more likely to occur in only

[54] EPU or News data are available at https://www.policyuncertainty.com/. The CPI is for the U.S. urban consumers' payment on food, and its base year is from 1982 to 1984. The PPI is for the U.S. food manufacturing industry, and its base year is 1984.
[55] DXY is an index of the value of U.S. dollars relative to a basket of its trade partners' currencies. It is a daily index and is collected from Barchart.
[56] We take VIX as an example to explain how we calculate an indicator variable for large shocks. We first calculate the returns of VIX and then sort these returns from the smallest to the largest to define the 0.95 quantile of its distribution as a threshold for large shocks. The indicator variable takes the value of one if the return on VIX is above this 0.95 quantile threshold and zero otherwise. We construct the indicator variable for small shocks in a similar way using the 0.05 quantile.

one market for the crop pairs and in two markets for the livestock pair. The percentage of a single exceedance in the corn-soybean pair is almost twice as high as the corresponding percentage in the wheat pair, regardless of whether it pertains to return or volatility. This finding aligns with the fact that the corn and soybean markets are more active and volatile compared to the wheat market. According to the CME group, corn and soybean futures are among the most liquid commodity futures, with 350,000 and 200,000 contracts traded per day, respectively.

Additionally, the percentage of two exceedances in the hog-cattle-feeder cattle pair is 2.44%, 2.72%, and 2.48% for the upper-tail coexceedance, lower-tail return coexceedance, and volatility coexceedance, respectively. These figures are approximately 3.71, 2.91, and 3.69 times lower than the percentage of a single exceedance in the upper-tail return, lower-tail return, and volatility, respectively.

Upper-tail return coexceedances are seldom, with percentages of 1.87%, 3.03%, and 0.36% for corn-soybean, winter wheat-spring wheat, and lean hogs-live cattle-feeder cattle pairs, respectively. On the other hand, the percentages of low-tail return coexceedances are slightly larger, with 1.97% for corn and soybean, 3.10% for winter wheat and spring wheat, and 0.55% for lean hogs, live cattle, and feeder cattle. Of these three pairs, winter what-spring wheat has the largest percentage of coexceedances in both tails, indicating the extreme price movements in wheat markets are highly related. Similarly, the percentage of volatility coexceedances are the highest in the wheat markets. The percentage of coexceedance in the wheat pair is 2.78%, which is 1.41 and 9.59 times larger than the corresponding percentages in corn-soybean pair (1.97%) and hog-cattle-feeder cattle pair (0.29%).

Coexceedance counts on USDA report release days

We present the percentage of exceedance counts in figures 4.1-4.4. These counts are calculated by dividing the frequency of $W_t^J = h$ on release days, where *J*=*CS*, *WSW*, *LLF* and $h = 0, 1, 2$ for the corn-soybean and winter-spring wheat pairs, and $h = 0, 1, 2, 3$ for the hog-live cattle-feeder cattle pair, by the total number of release days for each report cluster. The figures depict the percentage of both upper-tail return and lower-tail return exceedances.

For example, in the ACR and GS report cluster, there are 29 release days, and 31.03% of those days exhibit lower-tail exceedance in one market, while 10.71% exhibit lower-tail exceedance in two markets. Comparing the exceedance counts across report clusters, extremely low returns in one market occur more frequently on the release days of ACR and GS reports (31.03%), and less frequently on the release days of the WASDE report (10.10%) in the corn-soybean pair. The highest percentage of upper-tail coexceedance in two markets is observed on the release day of the January cluster of CPAS, WASDE, and GS reports (14.29%), while the lowest percentage is observed on the release day of the WASDE report only (0.05%). For the winter-spring wheat pair, both lower- and upper-tail return coexceedances are more likely to occur on the release days of PP and GS reports, with percentages of 17.85% and 10.71%, respectively.

Figure 4.3 displays the exceedance counts for the livestock pair. Regardless of the upper or lower tail, single exceedances occur more frequently on the release days of HP reports (12.5% for the lower tail and 13.97% for the upper tail), while three coexceedances occur more frequently on the release days of COF reports, with 1.73% of observations below the 5% threshold and 1.44% of observations above the 95% threshold.

Similarly, the counts for volatility exceedance across report clusters are shown in figure 4.4. Either the ACR and GS report cluster or the PP and GS report cluster witness the highest percentage of one or two volatility exceedances, while the WASDE report only witnesses the smallest percentage in both crop pairs. Additionally, volatility (co)exceedances are more likely to occur on the release days of COF report than the HP report.

Impacts of USDA reports on return coexceedances

Using the estimation results from equation (4.6), we present the average marginal effects of USDA reports on the lower tail (5%) and upper tail (95%) of returns in table 4.5.[57] The average marginal effects indicate the average change in the probability of coexceedance occurrences if one explanatory variable has a one-unit change, while holding all other variables constant. The explanatory variables for USDA reports indicate the trading days when the reports within the same cluster are released. Therefore, the average marginal effects of USDA reports describe the difference in the probability of coexceedance occurrences between release and non-release days.

As shown in table 4.5, the marginal effects with statistically significance levels at 10% or lower are positive, indicating that the release of USDA reports always increases the occurrence of extreme returns in corn and soybean markets. Four out of six report clusters significantly increase the probability of one or two exceedances in both tails. The cluster of ACR and GS reports has the largest impact, with the probability of extremely low (negative) returns occurring in any one of the markets increasing by 0.228, and the probability of joint occurrence increasing by 0.129. The cluster of WASDE and CP reports has the smallest impact, with an increase in the

[57] Since our main focus is to determine whether USDA reports play a role in the occurrence of extreme returns or volatility, we only present their associated results in the manuscript and report the results for the other determinants of coexceedances in the appendix tables C.1-C.3.

probability of one exceedance by 0.095 and that of two exceedances by 0.038 in the lower tail. On the other hand, the marginal effect of the CPAS, WASDE, and GS cluster on the occurrence of coexceedances in the upper tail is almost indifferent to that of the ACR and GS, with an increase of 0.215 and 0.127 in the probability of one and two exceedances, respectively. In the upper tail, the WASDE report has the smallest marginal effect, with the probability of one exceedance increasing by 0.031 and that of two exceedances increasing by 0.012.

For the winter and spring wheat pair in table 4.6, the marginal effects of the ACR and GS cluster are very close to those of the PP and GS cluster in the lower tail, as both clusters increase the probability of extremely low returns. Similar to the corn-soybean pair, the cluster of WASDE and CP reports has the smallest significant impact on the coexceedance probability in both tails. Moreover, the release of USDA reports is more likely to increase the probability of extremely low returns rather than extremely high returns. For a given report cluster, the marginal effects are consistently larger in the lower tail than in the upper tail.

Similar to the results in grains and oilseed markets, selected USDA reports also increase the probability of return exceedances in livestock markets (table 4.7). However, the magnitude of these effects is relatively low compared to the grains. The largest increase in the exceedance probability is only 0.046 on the release days of the HP report. In addition, we find that the probability of all three livestock markets simultaneously suffering from extremely low returns is not significantly influenced by the release of HP or COF reports, but the release of HP report significantly increases the joint occurrence of extremely high returns by 0.002. Moreover, the COF report does not have any impact on the occurrence of upper-tail coexceedances.

Impacts of USDA reports on volatility coexceedances

We also examine the marginal effects of USDA reports on the probability of coexceedances in absolute returns, as higher absolute returns indicate higher volatility. Given that existing literature suggests an increase in futures return volatility on USDA report release days, we focus on the occurrence of volatility exceedances only in the upper tail (i.e., absolute returns above the 0.95 quantiles of their distributions). The corresponding marginal effects are presented in tables 4.8-4.10.

For the corn-soybean pair (table 4.8), all report clusters, except for the WASDE report released outside the growth cycle of corn and soybean, significantly increase the probability of extremely high volatility in one or more markets. The heightened probability of volatility coexceedances on release days indicates a deviation from market expectations. Increased volatility in investment portfolios may create arbitrage opportunities, as price fluctuations can lead to disparities between the current futures price and the intrinsic value of an agricultural commodity.

However, the direction of returns decides whether information releases create short-run arbitrages for traders to make a profit. Moreover, the effects of report releases are also related to trading strategies. For instance, new information, which increases returns, indicates good news for long-position traders but bad for short-position ones. Pardo and Torro (2007) extend good or bad news to more detailed types by considering the volatility responses. Higher returns associated with increased volatility suggest that the report release can be regarded as good news for traders who hold the positions while lower returns with heightened volatility imply very bad news for them as they cannot manage their risks through a combination of substitutes on the release day. As shown in table 4.5, all five report clusters also increase the probability of lower-tail return exceedances, with four of them increasing the probability of upper-tail return exceedances in the corn-soybean pair. Except for the GS report, the other four report clusters (CPAS, WASDE, and GS reports; WASDE and CP reports; PP and GS reports; and ACR and GS reports) have a dual effect of bringing either good news (i.e., unexpected positive returns accompanied by increased volatility) or very bad news (i.e., unexpected negative returns accompanied by increased volatility). Thus, traders might either benefit or incur losses by simultaneously holding corn and soybean futures. Among these four clusters, traders who hold the corn-soybean portfolio are more likely to obtain profits on the release days of WASDE and CP reports, as their marginal effects on upper-tail return (co)exceedances are much higher than those in lower-tail coexceedances. On the other hand, the release of the GS report only increases the occurrence of lower-tail return coexceedances, implying a higher probability of a loss on the release days of GS reports.

Regarding winter and spring wheat (table 4.9), five out of six report clusters significantly increase the probability of volatility exceedances, but only two of them have an impact on the occurrence of a single exceedance. Similar to the corn-soybean pair, WASDE reports released outside the growth cycle of wheat do not affect the probability of extreme volatility occurrences. The report effects are relatively smaller in wheat markets compared to corn and soybean markets. For example, the cluster of PP and GS reports increases the probability of one (two) volatility exceedance(s) in the corn-soybean pair by 0.261 (0.182), whereas it only increases those in the wheat pair by 0.144 (0.153). These findings align with previous studies that have shown muted price and volatility reactions to USDA reports in wheat markets compared to corn and soybean markets (Karali et al. 2019; Isengildina-Massa et al. 2021).

In the case of livestock markets (table 4.10), only the release of the COF report increases the probability of volatility exceedances, with the probability decreasing as the number of exceedances increases. Karali, Isengildina-Massa, and Irwin (2019) find evidence of decreasing market reactions to market surprises brought by these two reports after 2010. Our findings regarding the impacts of the HP and COF reports partially align with this previous work, as we do not observe a significant impact of the HP report in increasing the probability of volatility (co)exceedances. It is difficult to draw a conclusion regarding the role of HP reports for traders holding this livestock complex since they cannot simultaneously increase the probability of return and volatility (co)exceedances. However, for COF reports, we find evidence that their release leads to the occurrence of extremely low returns in one or two markets with high volatility. This suggests that traders with hog-cattle-feeder cattle portfolios are likely to partially lose their gains on the release day of COF reports.

Realized volatility coexceedances surrounding report release times

Since January 2013, USDA has been releasing major crop reports during the trading hours of futures markets at 11 am CT. This provides us a valuable opportunity to analyze the detailed impacts of these reports on coexceedance occurrences using intraday data. Our analysis focuses on realized volatility, which is the square root of the sum of squared returns at high sampling frequency.[58] In the literature, researchers have found that a five-minute sampling frequency is optimal for mitigating the bias caused by microstructure noises in high-frequency data (e.g., Ghysels and Sinko 2011; Bollerslev, Li, and Zhao 2020). Consequently, we capture return

[58] Because conditional volatility is unobservable, Andersen et al. (2003) suggest measuring price volatility over a fixed interval as the square root of the sum of squared returns at high sampling frequency, termed as realized volatility.

variation within each five-minute interval and calculate realized volatility (RV) for each commodity using one-minute bar prices.

To calculate RV, we first compute the one-minute return, $r_{i,j,d}$, for commodity *i* as:

(4.7) $r_{i\ell t} = ln(p_{i\ell t}) - ln(p_{i,\ell-1,t})$.

Here, *i* represents the commodities and $p_{i\ell t}$ is the price of commodity *i* at the ℓ^{th} minute on day *t*. The five-minute realized volatility on day *t* (RV_{iqt}) is the square root of the sum of squared one-minute returns within the interval [ℓ−5, ℓ],

(4.8) $RV_{iqt} = \sqrt{\sum_{m=0}^{4} r_{i,\ell-m,t}^{2}}$,

where subscript *q* denotes the five-minute interval.

To analyze the changes in occurrence of extremes before and after the release time, we calculate the percentage of exceedance counts at different levels (*h* = 0,1, 2) on the release days of each cluster during day trading sessions.[59] The proportion (percentage) of each exceedance outcome is determined by dividing the frequency of a specific outcome by the total observations at a given time point. A higher proportion indicates a greater likelihood of observing a specific type of coexceedance (either zero, one, or two coexceedances) at that time point.

In figures 4.5-4.6, the vertical axis represents the percentage of exceedance outcomes, ranging from 0% to 100%. The horizontal axis represents time during trading hours. The

[59] CME Group adjusts the CBOT grain trading hours according to customer feedback. In our sample period, there are two adjustments made. Beginning on April 8, 2013, there is a break added to the electronic trading from 7:45 am CT to 8:30 am CT, and CME Globex day-trading session ends earlier at 1:15 pm CT but the overnight trading opens later at 7:00 pm CT on weekdays. Since July 6, 2015, the end of trading hours has been further expanded to 1:20 pm CT. In our analysis, we focus on the day-trading hours from 8:30 am to 1:20 pm CT.

colored lines represent two outcomes: one exceedance (dark grey) and two exceedances (black). The pattern and shapes of these colored lines provide insights into the changes in the probability of coexceedances over time.

Figure 4.5 shows the results for the corn-soybean pair. All selected report clusters exhibit a similar pattern: the line representing two exceedances peaks at 100% at 11:00 am CT, indicating that intra-day coexceedance always occurs when the report is released. Additionally, each cluster shows different persistence in volatility coexceedance. The line representing two exceedances for the CPAS, WASDE, and GS reports drops sharply to zero within 30 minutes after the release time, while for the ACR and GS reports, it persists slightly longer until noon. These findings are consistent with previous studies suggesting that the absorption of USDA announcement shocks is relatively quick in the real-time era (Adjemian and Irwin 2018). We also confirm that two markets simultaneously experiencing large volatility are more likely to occur from 11:00 am to 11:30 am CT.

In the wheat markets (figure 4.6), volatility coexceedance also peaks at the release time of each cluster. However, volatility coexceedances at the release time only occur on 80% of the release days of the clusters of WASDE and CP reports or PP and GS reports. This implies that the intra-day market reactions to USDA reports in wheat markets are less intense compared to corn and soybean markets.

Conclusions

USDA reports are an important source of fundamental information on major agricultural commodities. Previous studies have found that their releases lead to price and volatility spikes in single agricultural commodity markets. The same USDA reports include information for multiple agricultural commodities, especially for crops. In addition, agricultural commodities often serve as substitutes for each other in their usage. For instance, corn and soybean can be used for animal feeds and as raw materials for biofuels. If corn prices rise significantly, livestock producers might switch to soybeans since they are alternative feed sources. In futures markets, the dynamic intermarket price relationships, such as intermarket spreads or corn-to-soybean price ratio, are usually used for risk management or for speculative trading.[60] Therefore, our study focuses on the extreme returns and volatility in the markets of agricultural substitutes and investigates the role of USDA reports in the occurrence of such extreme events. It aims to provide new insights into the empirical linkages between market reactions and public information.

We find statistical evidence of an increased probability of return and volatility coexceedances on the release days. Compared to USDA reports for livestock, grain reports have a larger impact on coexceedances. Specifically, the magnitude of their report effects varies by the type of information contained in the reports. The release of ACR and GS reports in June has the largest impact on the occurrence of return coexceedances in the lower tail of the corn-soybean pair, while its impact on the upper-tail return coexceedances is same as the January release of the CPAS, WASDE, and GS reports. For the wheat pair, the cluster of ACR and GS reports is also one of the two clusters with the largest impact on the lower-tail return coexceedances, and the other cluster is PP and GS reports. More importantly, the cluster of ACR and GS reports is always the most significant report in increasing the likelihood of volatility coexceedances in crop pairs. These findings are not surprising since the largest survey the NASS

[60] The corn-soybean price ratio is a significant indicator for farmers to measure the relative profitability of corn and soybean in making their decisions about crop rotations (USDA 2020; CME 2022b).

conducts each year is the June Agricultural Survey (Vogel and Bange 1999). During the first two weeks in June, farmers report their acreage planted by crop and the expected harvest acreage, and the ACR reports contain these survey responses. Our results show that coexceedances are more likely to occur on the release days of ACR, indicating that the ACR brings new information about planted acreage and harvested acreage at the beginning of the marketing year.

Moreover, we observe that USDA reports play a dual role for portfolio traders, particularly spread traders, who can either capitalize on profit or face losses in crop markets. However, it is important to be aware of the downside risks brought by the release of GS reports in September for the corn-soybean pair, the release of PP and GS reports for the wheat pair, and the release of the COF report for the livestock pair. We only observe their impacts on an increase in the lower-tail (co)exceedances associated with a higher probability of elevated volatility. These situations indicate that trading strategies based on price relationships among each substitute pair might be challenging and risky on the release days of corresponding reports.

More importantly, an increased probability of return and volatility coexceedances on the release days implies that the release of fundamental commodity information is a significant driver of extreme price movements analogous to flash crashes in agricultural commodity markets. In particular, the growing number of automated, algorithmic, and high-frequency trades makes the futures market susceptible to extreme fluctuations. The release of new information can be a double-edged sword to improve market transparency and efficiency but trigger extreme price and volatility comovements. Therefore, it is essential for market participants to efficiently and correctly interpret the information contained in government reports.

Table 4.1. Summary Statistics

	Grain and Oilseeds				Livestock		
	S	C	SW	W	LH	LC	FC
$r_{i,t}$							
Mean	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Std. Dev.	1.73	1.56	1.90	1.54	2.28	1.03	1.13
Min	-27.44	-22.47	-11.45	-26.21	-21.85	-6.01	-9.55
Max	8.68	7.89	10.53	6.68	27.81	8.31	7.83
Skewness	-0.88	-0.43	0.16	-1.66	1.36	0.05	-0.22
Kurtosis	17.92	11.24	5.20	24.47	26.87	6.41	10.92
5% quantile	-2.57	-2.29	-2.85	-2.24	-3.06	-1.65	-1.67
95% quantile	2.69	2.47	3.17	2.27	2.95	1.63	1.74
$\lvert r_{i,t}\rvert$							
Mean	1.21	1.14	1.43	1.07	1.43	0.74	0.77
Std. Dev.	1.24	1.07	1.26	1.11	1.77	0.71	0.82
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	27.44	22.47	11.45	26.21	27.81	8.31	9.55
Skewness	3.85	2.97	1.94	4.77	5.36	2.14	3.19
Kurtosis	47.11	30.18	8.95	66.39	51.64	11.16	21.11
95% quantile	3.53	3.14	3.83	3.01	3.88	2.14	2.21
Observation	7222	7222	7222	7222	7218	7218	7218

Notes: The sample period is from May 1994 to December 2022, where the announcement of USDA reports affects the same day trading. $p_{i,t}$ represent settlement prices of each commodity *i* on day *t*. *C, S, SW, W, LC, FC,* and *LH* represents corn, soybean, winter wheat, spring wheat, live cattle, feeder cattle and lean hogs, respectively.

Table 4.2. USDA Reports for Selected Agricultural Commodities, 1994-2022

USDA Report	Content	Release Frequency	Release Days	Release Time
CPAS	Crop production data for the past year and information on area planted and harvested, yield, and production for corn, soybean, and wheat	Annually	Between the 10th and 13th of January, except for 2019 (Feb. 8) and 1994 (Jan. 1)	7:30 am CT (May 1994-December 2012); 11:00 am CT (January 2013- present)
SGAS	Acreage, area planted and harvested, yield and production data for wheat	Annually	Usually the last week of September, except for 1994 (Sep. 1), 2001(Oct. 1), and 2005 (Oct. 3)	7:30 am CT (May 1994-December 2012); 11:00 am CT (January 2013- present)
WWS	Annual seeded acreage of winter wheat, durum wheat, and rye crops	Annually	Between the 10th and 12th of January, except for 2019 (Feb. 8) and 1996 (Jan. 16)	7:30 am CT (May 1994-December 2012); 11:00 am CT (January 2013- present)
PP	Expected plantings and last year's harvest for corn, soybean, corn, and all wheat	Annually	Between the 28th and 31st of March	7:30 am CT (May 1994-December 2012); 11:00 am CT (January 2013- present)
ACR	Acreage or harvested for corn, soybeans, and wheat	Annually	Between the 28th and 30th of June	7:30 am CT (May 1994-December 2012); 11:00 am CT (January 2013- present)
GS	Stocks of corn, soybeans, and wheat by position (on-farm or off-farm storage)	Quarterly	Between the 10th and 12th of January, and at the end of March, June, and September	7:30 am CT (May 1994-December 2012); 11:00 am CT (January 2013- present)

(Continuous)

HP	U.S. pig crop for 16 major states and the U.S.	Quarterly (Monthly Jan.2001-Sep. 2003)	Fridays near the end of March, June, September, and December	2:00 pm CT, except for 12:00 pm CT in December 2011, and at 11:00 pm CT in March and December 2016
COF	Total number of cattle and calves on feed, placements, marketings, and other disappearances	Monthly	Friday on the third week of each month	2:00 pm CT, except for December 2005 (12:00 pm CT), May 2015, and December 2016 (11:00 am CT)
WASDE	U.S. and world supply and use balances of major grains	Monthly	Between the 9th and 12th of each month	7:30 am CT (May 1994-December 2012); 11:00 am CT (January 2013- present)
CP	Crop production data for the U.S., including acreage, area harvested, and yield	Monthly	Between the 9th and 12th of each month (Only provide information based on growth cycle)	7:30 am CT (May 1994-December 2012); 11:00 am CT (January 2013- present)

Notes: CPAS=Crop Production Annual Summary, SGAS=Small Grains Annual Summary, WWS=Winter Wheat Seedings (it includes three annual reports of wheat: Winter Wheat and Rye Seedings for1994-1999, Winter Wheat Seedings for 2000-2016, and Winter Wheat and Canola Seedings for 2017-2022), PP=Prospective Plantings, ACR=Acreage, GS=Grain Stocks, HP=Hogs and Pigs, COF=Cattle on Feed, WASDE=World Agricultural Supply and Demand Estimates, CP=Crop Production.

Table 4.3. USDA Report Clusters for Grains and Livestock

USDA report cluster	Release months	Number of release days
1) Corn and Soybean		
CPAS+WASDE+GS	January	28
WASDE	February, March, April, May, June, July, December	198
WASDE +CP	August, September, October, November	115
PP+GS	March	28
ACR+GS	June	29
GS	September	29
2) Winter and Spring Wheat		
CPAS+WASDE+GS+WWS	January	28
WASDE	February, March, April, September, October, December	197
WASDE +CP	May, June, July, August	116
PP+GS	March	28
ACR+GS	June	29
GS+SGAS	September	26
3) Livestock		
HP	March, June, September, and December	136
COF	All months	347

Notes: For each commodity pair, report clusters that are released simultaneously are presented along with their release months. Our sample period is from May 1994 to December 2022.

Table 4.4. Contemporaneous Occurrence of Extreme Events in the Tails

	Corn and Soybean (*CS*)			Winter and Spring Wheat (*WSW*)			Lean Hogs, Live Cattle, and Feeder Cattle (*LLF*)			
Number of exceedances	0	1	2	0	1	2	0	1	2	3
UR_t^J	6640	440	142	6722	276	224	6364	652	176	26
	(91.83%)	(6.30%)	(1.87%)	(93.01%)	(3.96%)	(3.03%)	(88.17%)	(9.03%)	(2.44%)	(0.36%)
LR_t^J	6632	455	135	6717	286	219	6411	571	196	40
	(91.94%)	(6.09%)	(1.97%)	(93.08%)	(3.82%)	(3.10%)	(88.82%)	(7.91%)	(2.72%)	(0.55%)
UV_t^J	6640	440	142	6700	321	201	6356	662	179	21
	(91.94%)	(6.09%)	(1.97%)	(92.77%)	(4.44%)	(2.78%)	(88.06%)	(9.17%)	(2.48%)	(0.29%)

Notes: Table reports the frequency of UR_t^J, LR_t^J, and UV_t^J calculated in equations (4.2)-(4.4) for upper-tail return (co)exceedances, lower-tail return (co)exceedances, and volatility (co)exceedances, respectively. The number of exceedances indicates how many markets have extreme price or volatility movements in a given time *t* in each pair. *J* represents the pair for corn-soybean, spring-and-winter wheat, and hog-cattle-feeder cattle, where *J=CS*, *WSW*, or *LLF*. The percentages are in parentheses. Total observations for corn-soybean and winter-spring pair are 7222, while total observation for lean hog-live cattle-feeder cattle pair is 7218.

Table 4.5. Effects of USDA Reports on Return Coexceedance: Corn and Soybean

	Lower tail (5%)		Upper tail (95%)	
	One exceedance	Two exceedances	One exceedance	Two exceedances
CPAS+WASDE+GS	0.168***	0.079**	0.215***	0.127***
	(0.053)	(0.036)	(0.046)	(0.048)
WASDE	0.019	0.006	0.031*	0.012*
	(0.016)	(0.006)	(0.017)	(0.007)
WASDE+CP	0.095***	0.038***	0.130***	0.060***
	(0.026)	(0.012)	(0.026)	(0.015)
PP+GS	0.212***	0.113***	0.129**	0.060*
	(0.047)	(0.042)	(0.053)	(0.032)
ACR+GS	0.228***	0.129***	0.215***	0.127***
	(0.043)	(0.044)	(0.045)	(0.047)
GS	0.194***	0.099***	0.030	0.012
	(0.049)	(0.039)	(0.045)	(0.018)

Notes: Table reports average marginal effects representing the difference in the probability of (co)exceedance occurrences between the release and non-release days of a given report cluster. The results are calculated using average marginal effects estimated in equation (4.6). Standard errors are given in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4.6. Effects of USDA Reports on Return Coexceedance: Winter and Spring Wheat

	Lower tail (5%)		Upper tail (95%)	
	One exceedance	Two exceedances	One exceedance	Two exceedances
CPAS+WASDE+GS+WWS	0.082**	0.089*	0.067**	0.071*
	(0.034)	(0.047)	(0.033)	(0.042)
WASDE	0.013	0.110	0.000	0.000
	(0.011)	(0.01)	(0.010)	(0.009)
WASDE+CP	0.050***	0.049***	0.031**	0.030*
	(0.018)	(0.018)	(0.017)	(0.017)
PP+GS	0.113***	0.135**	0.039	0.037
	(0.032)	(0.056)	(0.032)	(0.035)
ACR+GS	0.113***	0.135**	0.057*	0.058*
	(0.031)	(0.054)	(0.033)	(0.040)
GS+SGAS	0.044	0.042	0.029	0.028
	(0.033)	(0.036)	(0.033)	(0.034)

Notes: Table reports average marginal effects representing the difference in the probability of (co)exceedance occurrences between the release and non-release days of a given report cluster. The results are calculated using average marginal effects estimated in equation (4.6). Standard errors are given in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4.7. Effects of USDA Reports on Return Coexceedance: Lean Hogs, Live Cattle, and Feeder Cattle

	Lower tail (5%)			Upper tail (95%)		
	One exceedance	Two exceedances	Three exceedances	One exceedance	Two exceedances	Three exceedances
HP	0.038*	0.016*	0.003	0.046**	0.015*	0.002*
	(0.021)	(0.009)	(0.002)	(0.023)	(0.008)	(0.001)
COF	0.022*	0.009*	0.002	0.017	0.005	0.001
	(0.012)	(0.005)	(0.001)	(0.014)	(0.005)	(0.001)

Notes: Table reports average marginal effects representing the difference in the probability of (co)exceedance occurrences between the release and non-release days of a given report cluster. Average marginal effects are estimated in equation (4.6). Standard errors are given in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4.8. Effects of USDA Reports on Volatility Coexceedance: Corn and Soybean

	Upper tail (95%)	
	One exceedance	Two exceedances
CPAS+WASDE+GS	0.273***	0.205***
	(0.03)	(0.062)
WASDE	0.019	0.007
	(0.015)	(0.006)
WASDE+CP	0.164***	0.079***
	(0.026)	(0.017)
PP+GS	0.261***	0.182***
	(0.033)	(0.054)
ACR+GS	0.293***	0.280***
	(0.016)	(0.064)
GS	0.161***	0.080***
	(0.051)	(0.035)

Notes: Table reports average marginal effects representing the difference in the probability of (co)exceedance occurrences between the release and non-release days of a given report cluster. Average marginal effects are estimated in equation (4.6). Standard errors are given in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4.9. Effects of USDA Reports on Volatility Coexceedance: Winter and Spring Wheat

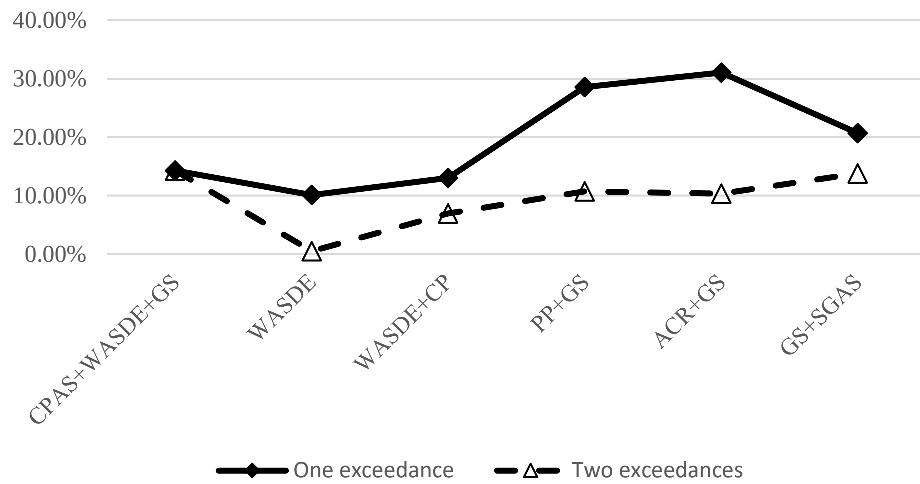
	Upper tail (95%)	
	One exceedance	Two exceedances
CPAS+WASDE+GS+WWS	0.066*	0.054
	(0.038)	(0.036)
WASDE	0.008	0.006
	(0.012)	(0.009)
WASDE+CP	0.052**	0.041**
	(0.018)	(0.016)
PP+GS	0.144***	0.153***
	(0.034)	(0.059)
ACR+GS	0.152***	0.167***
	(0.031)	(0.058)
GS+SGAS	0.075*	0.063
	(0.039)	(0.040)

Notes: Table reports average marginal effects representing the difference in the probability of (co)exceedance occurrences between the release and non-release days of a given report cluster. Average marginal effects are estimated in equation (4.6). Standard errors are given in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

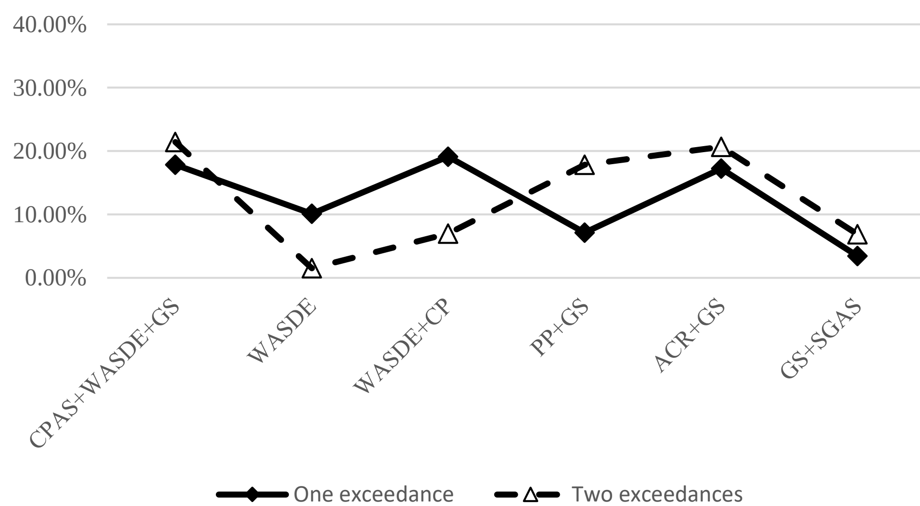
Table 4.10. Effects of USDA Reports on Volatility Coexceedance: Lean Hogs, Live Cattle, and Feeder Cattle

	Upper tail (95%)		
	One exceedance	Two exceedances	Three exceedances
HP	0.011	0.003	0.000
	(0.021)	(0.007)	(0.001)
COF	0.029**	0.010*	0.001*
	(0.014)	(0.005)	(0.001)

Notes: Table presents average marginal effects representing the difference in the probability of (co)exceedance occurrences between the release and non-release days of a given report cluster. The results are average marginal effects estimated based on equation (4.6). Standard errors are given in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.



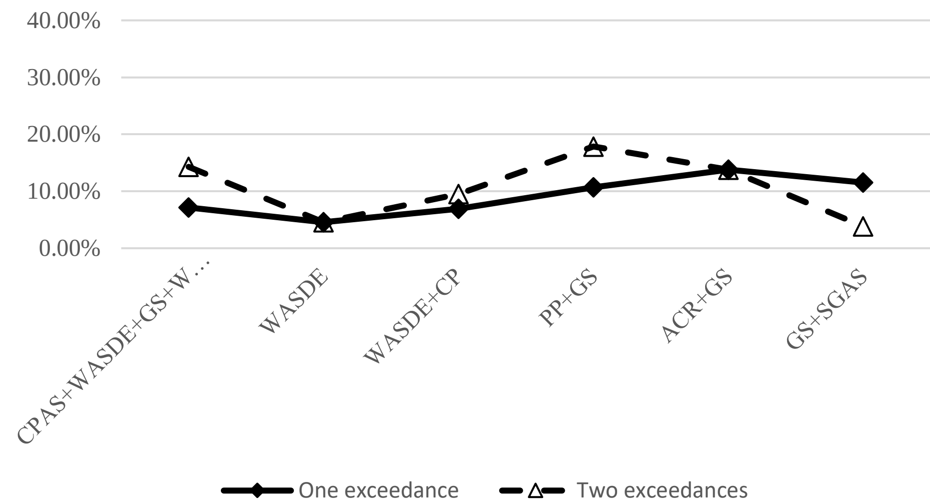
(a) Lower-tail (5%) coexceedances



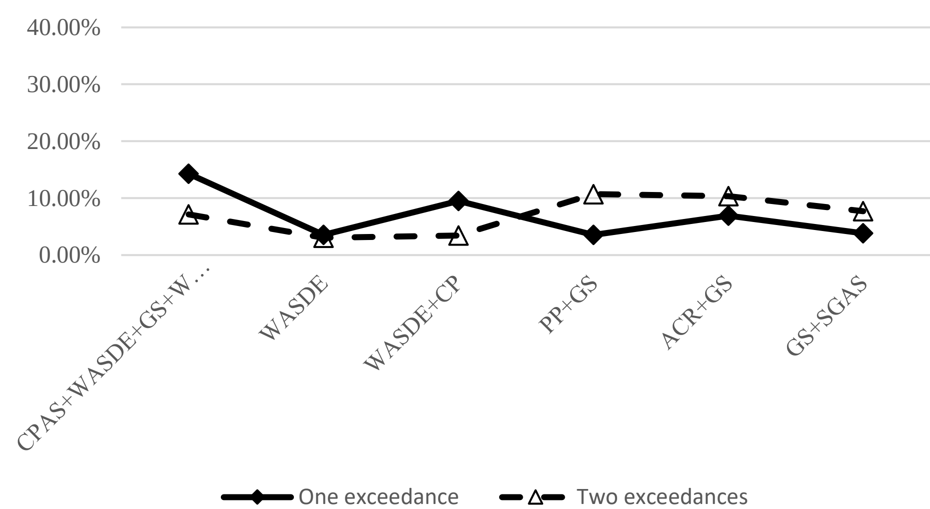
(b) Upper-tail (95%) coexceedances

Figure 4.1. Percentage of return exceedance counts in the corn-soybean pair on release days

Notes: The percentage of exceedance counts on release days is measured by dividing the frequency of exceedance counts at different levels by the total number of observations on release days of each cluster. The number of release days for each cluster is shown in table 4.3.



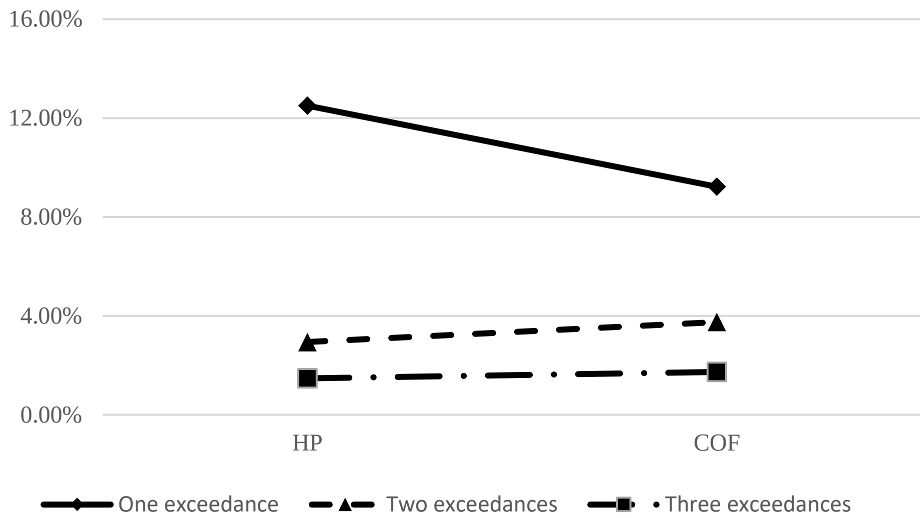
(a) Lower-tail (5%) coexceedances



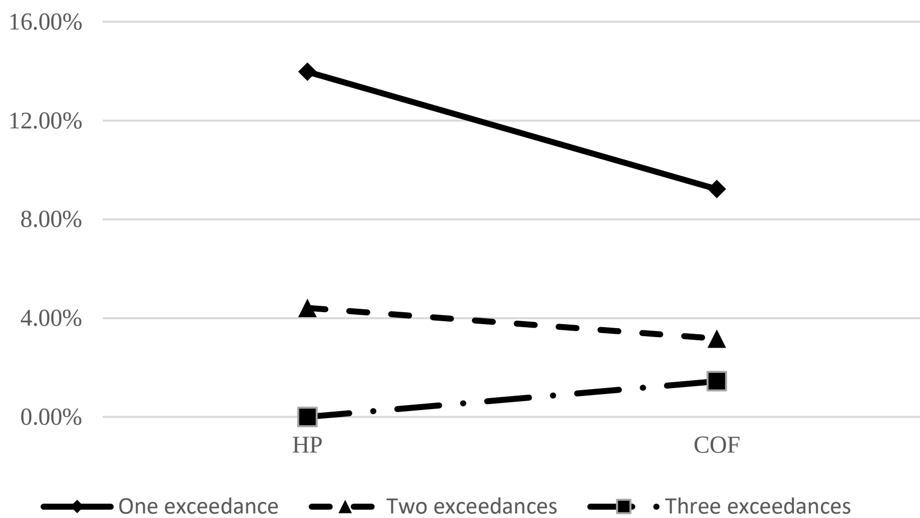
(b) Upper-tail (95%) coexceedances

Figure 4.2. Percentage of return exceedance counts in the winter-spring wheat pair on release days

Notes: The percentage of return exceedance counts on release days is measured by dividing the frequency of exceedance counts by the total number of observations on release days of each cluster. The numbers of release days for each cluster are shown in table 4.3.



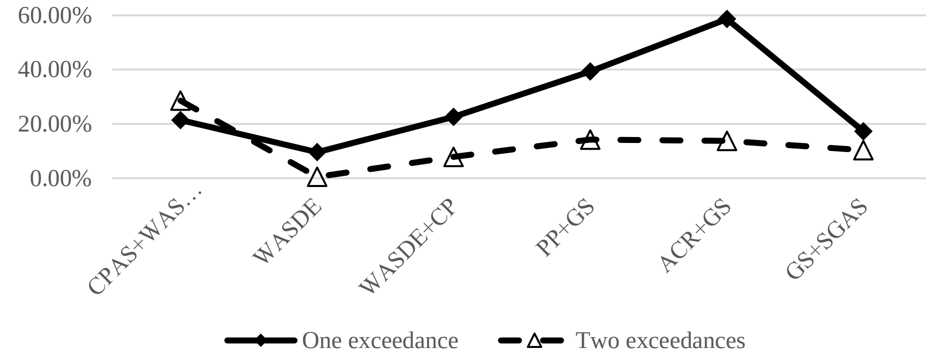
(a) Lower-tail (5%) coexceedances



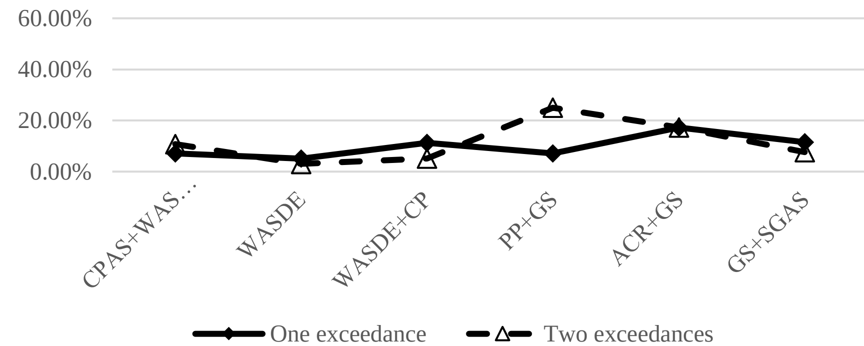
(b) Upper-tail (95%) coexceedances

Figure 4.3. Percentage of return exceedance counts in the hog-live cattle-feeder cattle pair on release days

Notes: The percentage of exceedance counts on release days is measured by dividing the frequency of exceedance counts by the total number of observations on release days of each cluster. The numbers of release days for each cluster are shown in table 4.3.



(a) Corn and soybean

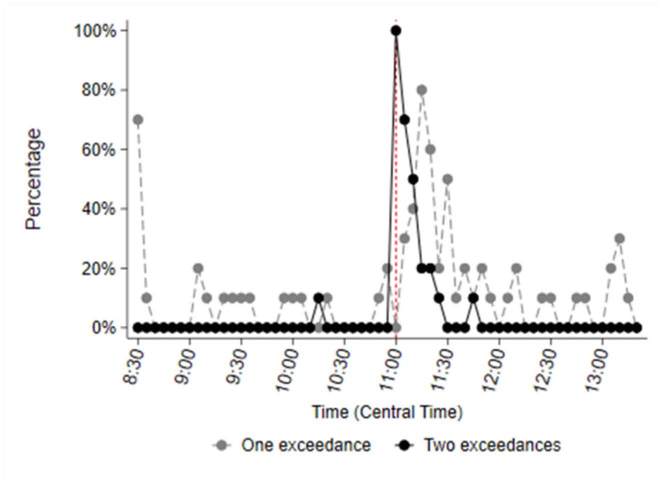


(b) Winter and spring wheat

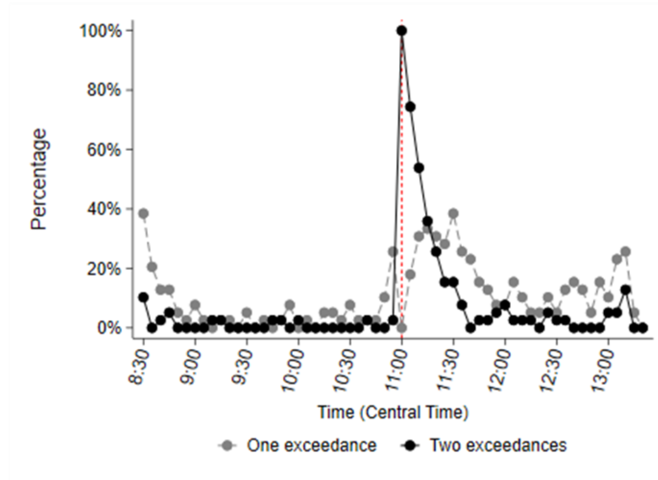
(c) Lean hog, live cattle, and feeder cattle

Figure 4.4. Percentage of volatility exceedance counts on release days

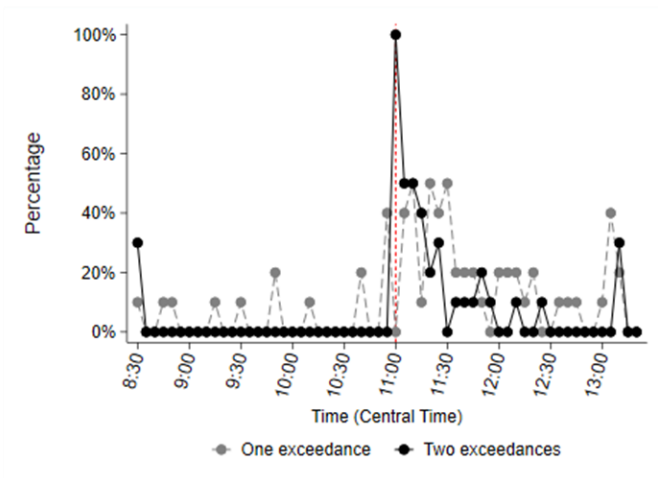
Notes: The percentage of exceedance counts on release days is measured by dividing the frequency of exceedance counts at different levels by the total number of observations on release days of each cluster. The numbers of release days for each cluster are shown in table 4.3.



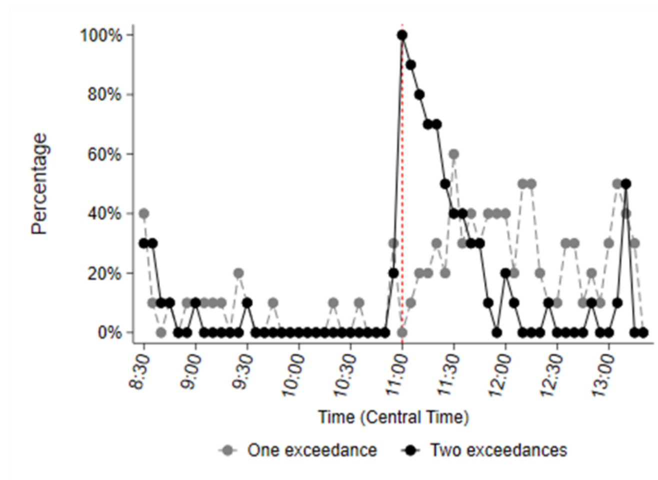
(a) CPAS, WASDE, and GS reports



(b) WASDE and CP reports



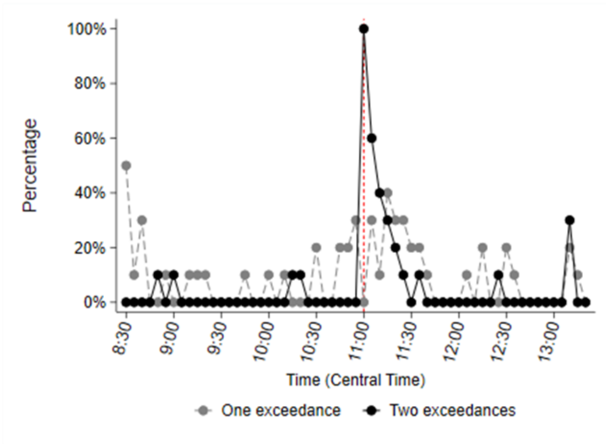
(c) PP and GS reports



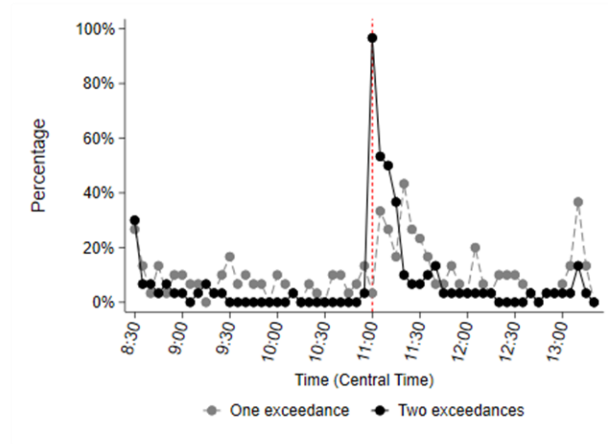
(d) ACR and GS reports

Figure 4.5. Percentage of realized volatility coexceedance in the corn-soybean pair on the release days of selected reports

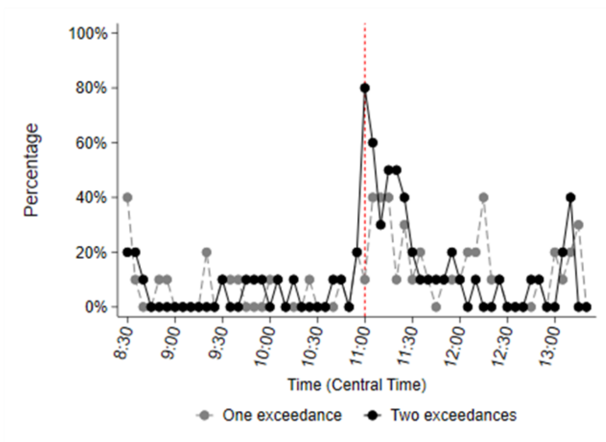
Notes: The spot represents the share of one or two exceedances from 8:30 am to 1:20 pm CT on the release days of selected reports. The vertical axis represents the percentage of each outcome on the total number of observations, while the horizontal axis represents the time. The red dash line is for the release time of USDA reports at 11:00 am CT.



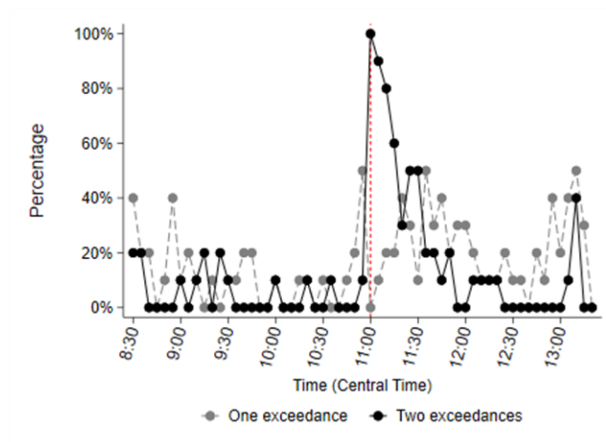
(a) CPAS, WASDE, GS, and WWS reports



(b) WASDE and CP reports



(c) PP and GS reports



(d) ACR and GS reports

Figure 4.6. Percentage of realized volatility coexceedance in the winter-and spring wheat pair on the release days of selected reports

Notes: The spot represents the share of one or two exceedances from 8:30 am to 1:20 pm CT on the release days of selected reports. The vertical axis represents the percentage of each outcome on the total number of observations, while the horizontal axis represents the time. The red dash line is for the release time of USDA reports at 11:00 am CT.

CHAPTER 5

CONCLUSIONS

In conclusion, this dissertation contributes to a better understanding of agricultural commodity markets by examining price and volatility dynamics from three distinct perspectives. There are three policy implications based on these findings. First, policymakers need to be aware of the interdependencies in global agricultural markets linked through food supply chains, particularly for major suppliers and consumers in the global markets. While a bilateral trade dispute can heavily impact exports/imports, its impact on volatility spillovers across countries is less significant than that of the global financial crisis.

Second, modern agricultural markets are often characterized as oligopolistic. The dependence of an end product's price response on the price level of the other end product is more pronounced in non-competitive markets. Price changes in downstream markets are not solely attributable to price shocks from upstream markets but can also result from the responses of jointly produced goods. Especially for the food industry, it is essential to have a proper understanding of price transmission from farms to tables. The full pass-through of decreasing agricultural prices can lead to discounted food prices and further benefit the low-income families struggling for food security. But it is questionable whether low-income families could benefit from the decreasing farm prices. Moreover, decreasing farm prices harms the incomes of farmers and ranchers and depresses their willingness to produce more goods in the long run. Policymakers should therefore explore and understand the price linkages among markets linked through supply chains before designing appropriate policies that ensure the welfare of market participants (i.e., farmers, processors, and food consumers) at each stage of supply chains.

Finally, the completeness and accuracy of the information that contributes to price determination have a significant impact on the decisions of buyers and sellers. Government reports providing supply-use information can be a double-edged sword to improve market transparency and efficiency but trigger extreme price movements analogous to flash crashes in agricultural markets. Therefore, traders or market participants might need extra guidance to utilize and interpret public reports for agricultural fundamentals effectively.

Overall, these policy implications emphasize the importance of understanding interdependencies, supply chain dynamics, and the role of information in agricultural commodity markets. By considering these factors, policymakers can make informed decisions and create a more efficient and resilient market environment.

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APPENDICES

A APPENDIX FOR CHAPTER 2

We expand the elements in matrix $\mathbf{H}_\mathrm{t}$ given in (2.6) and (2.7). The equations for conditional variances ($h_{MM,t}$, $h_{OO,t}$, $h_{SS,t}$) and covariances ($h_{MO,t}$, $h_{MS,t}$, $h_{OS,t}$) are given by:

(A.1) $$h_{MM,t} = (c_{MM}^2 + c_{OM}^2 + c_{SM}^2) + a_{MM}^2\varepsilon_{M,t-1}^2 + a_{OM}^2\varepsilon_{O,t-1}^2 + a_{SM}^2\varepsilon_{S,t-1}^2 + 2a_{MM}a_{OM}\varepsilon_{M,t-1}\varepsilon_{O,t-1} + 2a_{MM}a_{SM}\varepsilon_{M,t-1}\varepsilon_{S,t-1} + 2a_{OM}a_{SM}\varepsilon_{O,t-1}\varepsilon_{S,t-1} + b_{MM}^2h_{MM,t-1} + b_{OM}^2h_{OO,t-1} + b_{SM}^2h_{SS,t-1} + 2b_{MM}b_{OM}h_{MO,t-1} + 2b_{MM}b_{SM}h_{MS,t-1} + 2b_{OM}b_{SM}h_{OS,t-1} + \sum_{k=1}^{K}(g_{k,MM}^2 + g_{k,OM}^2 + g_{k,SM}^2)X_{k,t}$$

(A.2) $$h_{OO,t} = (c_{OO}^2 + c_{SO}^2) + a_{MO}^2\varepsilon_{M,t-1}^2 + a_{OO}^2\varepsilon_{O,t-1}^2 + a_{SO}^2\varepsilon_{S,t-1}^2 + 2a_{MO}a_{OO}\varepsilon_{M,t-1}\varepsilon_{O,t-1} + 2a_{MO}a_{SO}\varepsilon_{M,t-1}\varepsilon_{S,t-1} + 2a_{OO}a_{SO}\varepsilon_{O,t-1}\varepsilon_{S,t-1} + b_{MO}^2h_{MM,t-1} + b_{OO}^2h_{OO,t-1} + b_{SO}^2h_{SS,t-1} + 2b_{MO}b_{OO}h_{MO,t-1} + 2b_{MO}b_{SO}h_{MS,t-1} + 2b_{OO}b_{SO}h_{OS,t-1} + \sum_{k=1}^{K}(g_{k,OO}^2 + g_{k,SO}^2)X_{k,t}$$

(A.3) $$h_{SS,t} = c_{SS}^2 + a_{MS}^2\varepsilon_{M,t-1}^2 + a_{OS}^2\varepsilon_{O,t-1}^2 + a_{SS}^2\varepsilon_{S,t-1}^2 + 2a_{MS}a_{OS}\varepsilon_{M,t-1}\varepsilon_{O,t-1} + 2a_{MS}a_{SS}\varepsilon_{M,t-1}\varepsilon_{S,t-1} + 2a_{OS}a_{SS}\varepsilon_{O,t-1}\varepsilon_{S,t-1} + b_{MS}^2h_{MM,t-1} + b_{OS}^2h_{OO,t-1} + b_{SS}^2h_{SS,t-1} + 2b_{MS}b_{OS}h_{MO,t-1} + 2b_{MS}b_{SS}h_{MS,t-1} + 2b_{OS}b_{SS}h_{OS,t-1} + \sum_{k=1}^{K} g_{k,SS}^2 X_{k,t}$$

(A.4) $$h_{MO,t} = (c_{OM}c_{OO} + c_{SM}c_{SO}) + a_{MM}a_{MO}\varepsilon_{M,t-1}^2 + a_{OM}a_{OO}\varepsilon_{O,t-1}^2 + a_{SM}a_{SO}\varepsilon_{S,t-1}^2 + (a_{MM}a_{OO} + a_{MO}a_{OM})\varepsilon_{M,t-1}\varepsilon_{O,t-1} + (a_{MM}a_{SO} + a_{MO}a_{SM})\varepsilon_{M,t-1}\varepsilon_{S,t-1} + (a_{OM}a_{SO} + a_{OO}a_{SM})\varepsilon_{O,t-1}\varepsilon_{S,t-1} + b_{MM}b_{MO}h_{MM,t-1} + b_{OM}b_{OO}h_{OO,t-1} + b_{SM}b_{SO}h_{SS,t-1} + (b_{MM}b_{OO} + b_{MO}b_{OM})h_{MO,t-1} + (b_{MM}b_{SO} + b_{MO}b_{SM})h_{MS,t-1} + (b_{OM}b_{SO} + b_{OO}b_{SM})h_{OS,t-1} + \sum_{k=1}^{K}(g_{k,OM}g_{k,OO} + g_{k,SM}g_{k,SO})X_{k,t}$$

(A.5) $h_{MS,t} = c_{SM}c_{SS} + a_{MM}a_{MS}\varepsilon^2_{M,t-1} + a_{OM}a_{OS}\varepsilon^2_{O,t-1} + a_{SM}a_{SS}\varepsilon^2_{S,t-1} +$

$(a_{MM}a_{OS} + a_{MS}a_{OM})\varepsilon_{M,t-1}\varepsilon_{O,t-1} + (a_{MM}a_{SS} + a_{MS}a_{SM})\varepsilon_{M,t-1}\varepsilon_{S,t-1} +$

$(a_{OM}a_{SS} + a_{OS}a_{SM})\varepsilon_{O,t-1}\varepsilon_{S,t-1} + b_{MM}b_{MS}h_{MM,t-1} + b_{OM}b_{OS}h_{OO,t-1} +$

$b_{SM}b_{SS}h_{SS,t-1} + (b_{MM}b_{OS} + b_{MS}b_{OM})h_{MO,t-1} + (b_{MM}b_{SS} + b_{MS}b_{SM})h_{MS,t-1} +$

$(b_{OM}b_{SS} + b_{OS}b_{SM})h_{OS,t-1} + \sum_{k=1}^{K} g_{k,SM}g_{k,SS}X_{k,t}$

(A.6) $h_{OS,t} = c_{SO}c_{SS} + a_{MO}a_{MS}\varepsilon^2_{M,t-1} + a_{OO}a_{OS}\varepsilon^2_{O,t-1} + a_{SO}a_{SS}\varepsilon^2_{S,t-1} +$

$(a_{MO}a_{OS} + a_{MS}a_{OO})\varepsilon_{M,t-1}\varepsilon_{O,t-1} + (a_{MO}a_{SS} + a_{MS}a_{SO})\varepsilon_{M,t-1}\varepsilon_{S,t-1} +$

$(a_{OO}a_{SS} + a_{OS}a_{SO})\varepsilon_{O,t-1}\varepsilon_{S,t-1} + b_{MO}b_{MS}h_{MM,t-1} + b_{OO}b_{OS}h_{OO,t-1} +$

$b_{SO}b_{SS}h_{SS,t-1} + (b_{MO}b_{OS} + b_{MS}b_{OO})h_{MO,t-1} + (b_{MO}b_{SS} + b_{MS}b_{SO})h_{MS,t-1} +$

$(b_{OO}b_{SS} + b_{OS}b_{SO})h_{OS,t-1} + \sum_{k=1}^{K} g_{k,SO}g_{k,SS}X_{k,t}$

Table A.1. Futures Contracts Used in Constructing Price Series

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

Notes: DCE= Dalian Commodity Exchange; CBOT= Chicago Board of Trade. The subscript, 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 A.2. Summary Statistics of Futures Prices

	DCE Soybean Meal	DCE Soybean Oil	CBOT Soybean
Mean	9.629	5.229	10.624
Std. Dev.	1.719	1.298	2.515
Min	5.872	2.967	5.385
Max	14.762	9.622	17.683
Skewness	-0.016	0.699	0.308
Kurtosis	2.838	2.567	2.562
Observations	3256	3256	3256
ADF test	-2.633	-2.506	-2.553
Normality	3.706	290.979 ***	77.711 ***
White test	128.047 ***	764.957 ***	674.251 ***
ARCH effect	3229.222 ***	3241.312 ***	3228.252 ***
Ljung-Box(5)	15916.44 ***	16106.66 ***	15967.50 ***
Ljung-Box(25)	72791.71 ***	76950.99 ***	74425.82 ***

Notes: DCE= Dalian Commodity Exchange; 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 prices. White test is a heteroskedasticity test with the null hypothesis of homoskedasticity. ARCH effect is a Lagrange multiplier test for autoregressive conditional heteroskedasticity (ARCH) with the null hypothesis of no ARCH effects. Ljung-Box is an autocorrelation test with the null hypothesis of independently distributed returns. Five lags are used for the ADF, White, and ARCH effect tests; both five and twenty-five lags are used for the Ljung-Box test. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.3. MGARCH-X-BEKK Model Diagnostics: Full Sample Period

Model diagnostics I: Goodness of fit				
Log-likelihood	-12989.1			
AIC	8.024			
Degrees of freedom	7.618 ***			
	(0.291)			
Model diagnostics II: Residuals				
		DCE Soybean Meal (M)	DCE Soybean Oil (O)	CBOT Soybean (S)
Ljung-Box (5)		2.611	4.706	4.802
		[0.760]	[0.453]	[0.440]
Ljung-Box (10)		10.962	13.553	13.970
		[0.361]	[0.194]	[0.174]
Multivariate Q (5)	51.692			
	[0.229]			
Multivariate Q (10)	97.361			
	[0.280]			
Model diagnostics III: Squared residuals				
ARCH (5)		0.209	3.134	3.249
		[0.999]	[0.679]	[0.662]
ARCH (25)		4.856	13.357	20.850
		[1.000]	[0.972]	[0.701]

Notes: Diagnostics tests for the model in table 2.4 are presented. DCE= Dalian Commodity Exchange; CBOT= Chicago Board of Trade. AIC= Akaike information criterion. Ljung-Box and multivariate Q statistics test the independence of the residuals separately and jointly, respectively. Both five and ten lags are used for Ljung-Box and multivariate Q tests. Five and twenty-five lags are used for testing ARCH effects. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.4. MGARCH-X-BEKK: Transformed Conditional Variance Equation Parameters

	Var (M)	Var (O)	Var (S)
Constant	0.060 ***	0.017 **	0.007
	(0.015)	(0.007)	(0.007)
$\varepsilon^2_{M,t-1}$	0.019 ***	0.001	0.002
	(0.005)	(0.002)	(0.002)
$\varepsilon^2_{O,t-1}$	0.001	0.022 ***	0.010 *
	(0.001)	(0.007)	(0.005)
$\varepsilon^2_{S,t-1}$	0.004	0.007 **	0.025 ***
	(0.002)	(0.003)	(0.009)
$\varepsilon_{M,t-1}\varepsilon_{O,t-1}$	-0.008	-0.011 *	0.008
	(0.005)	(0.006)	(0.006)
$\varepsilon_{M,t-1}\varepsilon_{S,t-1}$	0.017 ***	-0.006	-0.012
	(0.004)	(0.005)	(0.010)
$\varepsilon_{O,t-1}\varepsilon_{S,t-1}$	-0.003	0.024 ***	-0.031 ***
	(0.003)	(0.005)	(0.011)
$h_{MM,t-1}$	0.989 ***	0.000	0.002 **
	(0.013)	(0.000)	(0.001)
$h_{OO,t-1}$	0.000	0.969 ***	0.004 ***
	(0.000)	(0.017)	(0.002)
$h_{SS,t-1}$	0.001 *	0.001	0.855 ***
	(0.001)	(0.000)	(0.024)
$h_{MO,t-1}$	0.028 **	0.005	0.006 **
	(0.014)	(0.013)	(0.002)
$h_{MS,t-1}$	-0.060 ***	0.000	0.078 ***
	(0.017)	(0.000)	(0.019)
$h_{OS,t-1}$	-0.001	-0.051 ***	0.122 ***
	(0.001)	(0.018)	(0.022)
Financial crisis	0.072 **	0.011	0.001
	(0.033)	(0.007)	(0.009)
Trade dispute	0.008	0.003	0.008
	(0.007)	(0.004)	(0.008)

Notes: The transformed coefficients on each term in the conditional variance equation (A.1)-(A.3) are presented with standard errors in parentheses. The sample period is From January 24, 2006 to December 31, 2019. DCE= Dalian Commodity Exchange; CBOT= Chicago Board of Trade. Subscripts M, S, and O represent DCE soybean meal, DCE soybean oil, and CBOT soybean, respectively. The asterisks *, **, and *** indicate Statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.5. Multivariate Structural Break for One Unknown Break Point

Null hypothesis	SupLR		WDmax	
No strucutral break	22.873 ***		22.873 **	
	The 95% Confidence Interval		The 90% Confidence Interval	
Estimated break				
858	483	1233	597	1119

Notes: The tests are proposed by Qu and Perron (2007). The alternative hypothesis of this test is the existence of one structural change point. The supLR tests against a fixed number of changes while the WDmax test is for an unknown number of changes up to some pre-specified maxima. The estimated break is selected by $seq(\ell+1|\ell)$ test. The number of observations are shown in results. The estimated break point, 858, represents the break date as 09/15/2009. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 2.5% level, respectively.

Table A.6. Summary Statistics of Synchronized Returns in Two Subperiods

	January 2006 - August 2009			October 2009 - December 2019		
	DCE Soybean Meal	DCE Soybean Oil	CBOT Soybean	DCE Soybean Meal	DCE Soybean Oil	CBOT Soybean
Mean	0.052	0.062	0.086	0.028	-0.020	0.012
Std. Dev.	1.606	1.635	1.880	1.038	0.986	1.259
Min	-8.216	-8.412	-7.411	-4.557	-4.645	-6.540
Max	6.719	5.434	6.445	5.754	4.852	6.366
Skewness	-0.343	-0.649	-0.332	0.077	0.022	-0.045
Kurtosis	5.321	5.677	4.636	4.696	4.210	4.989
Observations	848	848	848	2383	2383	2383
ADF test	-27.541 ***	-26.130 ***	-28.519 ***	-47.445 ***	-49.541 ***	-50.194 ***
Normality	206.953 ***	312.707 ***	110.128 ***	287.875 ***	145.572 ***	393.492 ***
White test	38.870 ***	70.718 ***	21.164 ***	78.315 ***	80.187 ***	250.797 ***
ARCH effect	77.310 ***	105.625 ***	60.523 ***	99.352 ***	41.732 ***	90.735 ***
Ljung-Box (5)	8.787	16.061 ***	1.252	8.123	6.123	9.111
Ljung-Box (25)	42.331 **	40.892 **	16.749	30.225	34.980 *	33.708

Notes: Returns are calculated as the percentage change in the settlement price from one day to the next. DCE= Dalian Commodity Exchange; 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-Ber test with the null hypothesis of normally distributed returns. White test is a heteroskedasticity test with the null hypothesis of homoskedasticity. ARCH effect is a Lagrange multiplier test for autoregressive conditional heteroskedasticity (ARCH) with the null hypothesis of no ARCH effects. Ljung-Box is an autocorrelation test with the null hypothesis of independently distributed returns. Five lags are used for the ADF, White, and ARCH effect test; both five and twenty-five lags are used for the Ljung-Box test. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.7. MGARCH-X-BEKK Model Diagnostics: Two Subperiods

Model diagnostics I: Goodness of fit	January 2006 - August 2009	October 2009 - December 2019
Log-likelihood	-3975.3	-8869.1
AIC	9.498	7.487
Degrees of freedom	9.292 ***	7.314 ***
	(1.358)	(0.525)

Model diagnostics II: Residuals		January 2006 - August 2009				October 2009 - December 2019		
		DCE Soybean Meal (M)	DCE Soybean Oil (O)	CBOT Soybean (S)		DCE Soybean Meal (M)	DCE Soybean Oil (O)	CBOT Soybean (S)
LB(5)		12.117	7.608	5.385		2.106	4.300	4.067
		[0.033]	[0.179]	[0.371]		[0.834]	[0.507]	[0.540]
LB(10)		14.563	11.398	5.846		9.650	11.362	15.212
		[0.149]	[0.327]	[0.828]		[0.472]	[0.330]	[0.125]
Multivariate Q(5)	31				43.103			
	[0.944]				[0.553]			
Multivariate Q(10)	70.71				81.793			
	[0.934]				[0.719]			
Model diagnostics III: Squared residuals								
ARCH(5)		3.019	3.149	1.116		0.229	3.180	3.248
		[0.697]	[0.677]	[0.953]		[0.999]	[0.672]	[0.662]
ARCH(25)		31.988	14.752	14.977		3.487	12.047	23.968
		[0.158]	[0.947]	[0.942]		[1.000]	[0.986]	[0.521]

Notes: Diagnostics tests for the model in table 2.5 are presented. DCE= Dalian Commodity Exchange; CBOT = Chicago Board of Trade. AIC= Akaike information criterion. Ljung-Box and multivariate Q statistics test the independence of the residuals separately and jointly, respectively. Both five and ten lags are used for Ljung-Box and multivariate Q tests. Five and twenty-five lags are used for testing ARCH effects. The asterisks *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.8. MGARCH-X-BEKK in Two Subperiods: Transformed Conditional Variance Equation Parameters

	January 2006 - August 2009			October 2009 - December 2019		
	Var (M)	Var (O)	Var (S)	Var (M)	Var (O)	Var (S)
Constant	0.239 ***	0.054 **	0.000	0.073 **	0.027 ***	0.000
	(0.085)	(0.023)	(0.000)	(0.032)	(0.010)	(0.000)
$\varepsilon^2_{M,t-1}$	0.226 **	0.002	0.014	0.019 **	0.000	0.010
	(0.095)	(0.005)	(0.022)	(0.007)	(0.001)	(0.007)
$\varepsilon^2_{O,t-1}$	0.046	0.033 **	0.020	0.002	0.009 *	0.011
	(0.033)	(0.015)	(0.015)	(0.002)	(0.005)	(0.008)
$\varepsilon^2_{S,t-1}$	0.026	0.002	0.000	0.006	0.008 *	0.059 ***
	(0.017)	(0.003)	(0.001)	(0.004)	(0.004)	(0.016)
$\varepsilon_{M,t-1}\varepsilon_{O,t-1}$	-0.204 *	-0.015	-0.033	-0.011	-0.004	0.020 *
	(0.109)	(0.025)	(0.036)	(0.007)	(0.005)	(0.011)
$\varepsilon_{M,t-1}\varepsilon_{S,t-1}$	-0.154 **	-0.003	-0.003	0.021 ***	-0.003	-0.047 **
	(0.073)	(0.008)	(0.015)	(0.005)	(0.005)	(0.023)
$\varepsilon_{O,t-1}\varepsilon_{S,t-1}$	0.069 **	0.015	0.003	-0.006	0.016 ***	-0.051 **
	(0.035)	(0.014)	(0.016)	(0.005)	(0.004)	(0.021)
$h_{MM,t-1}$	0.458 **	0.003	0.001	1.020 ***	0.000	0.006 **
	(0.230)	(0.006)	(0.004)	(0.026)	(0.000)	(0.003)
$h_{OO,t-1}$	0.053 *	1.021 ***	0.014	0.001	1.023 ***	0.006 **
	(0.028)	(0.046)	(0.010)	(0.001)	(0.020)	(0.002)
$h_{SS,t-1}$	0.002	0.000	0.875 ***	0.003	0.003	0.779 ***
	(0.008)	(0.001)	(0.069)	(0.002)	(0.002)	(0.041)
$h_{MO,t-1}$	0.311 ***	-0.101	-0.006	0.054 **	0.037	0.012 **
	(0.063)	(0.122)	(0.022)	(0.022)	(0.026)	(0.005)
$h_{MS,t-1}$	0.056	0.001	-0.044	-0.114 ***	-0.002	0.132 ***
	(0.112)	(0.002)	(0.159)	(0.036)	(0.002)	(0.030)
$h_{OS,t-1}$	0.019	-0.022	0.221 ***	-0.003	-0.114 ***	0.138 ***
	(0.045)	(0.057)	(0.081)	(0.002)	(0.036)	(0.025)
Financial crisis	0.082 *	0.087 *	0.000			
	(0.045)	(0.051)	(0.000)			
Trade dispute				0.014	0.023	0.040
				(0.017)	(0.093)	(0.082)

Notes: The transformed coefficients on each term in the conditional variance equation (A.1)-(A.3) are presented. Standard errors are in parentheses. DCE= Dalian Commodity Exchange; CBOT = Chicago Board of Trade. Subscripts M, S, and O represent DCE soybean meal, DCE soybean oil, and CBOT soybean, respectively. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

B APPENDIX FOR CHAPTER 3

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 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:

(B.1) $H_0: \gamma_S(\boldsymbol{\tau}^*) = 0, \boldsymbol{\theta}(\boldsymbol{\tau}^*) = \mathbf{0}$.

Figure B.1 presents the histogram of the *p*-values, associated with 729 *F*-statistics for the joint hypothesis tests in equation (B.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 ($\hat{\boldsymbol{\upsilon}}_{\mathrm{t}}$) 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.

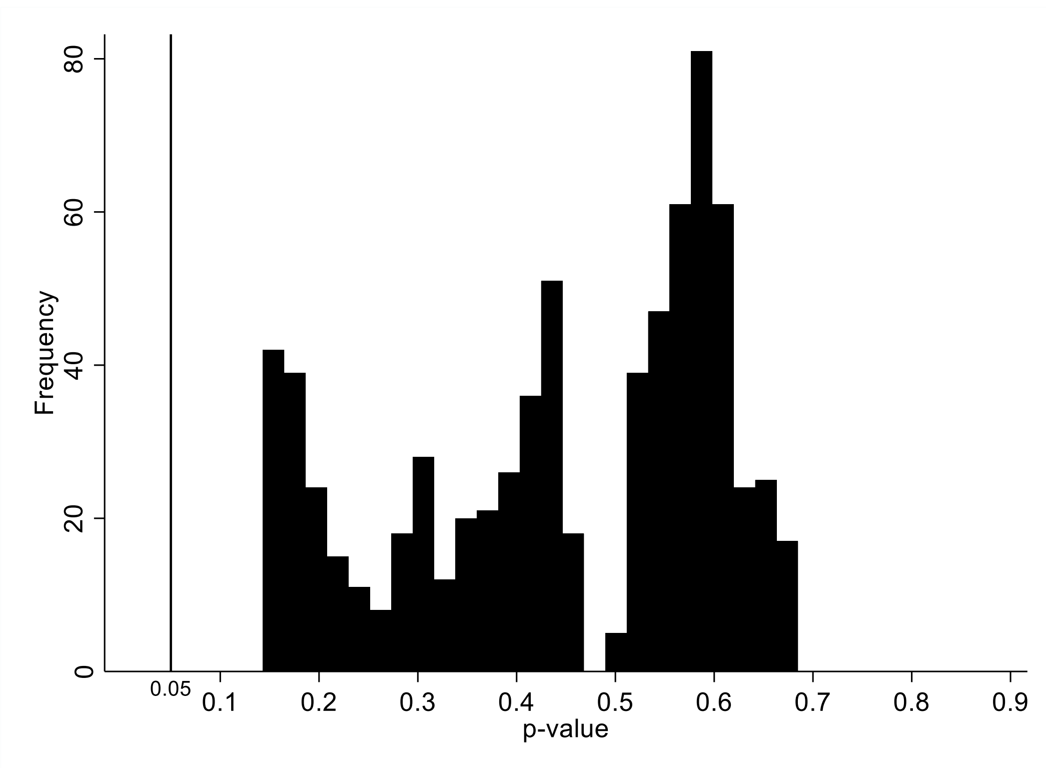

Figure B.1. Weak exogeneity tests for soybean log prices across multivariate quantiles
Notes: Tests of weak exogeneity of soybean log prices are carried out by estimating the marginal reduced-form model for soybeans based on a quantile regression. The histogram of the *p*-values for 729 null hypotheses given in equation (B.1) are plotted. The vertical line indicates the *p*-value of 0.05.

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.

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

		τ_O								
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	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.

Cumulative Price Responses to Soybean Price Changes

Table B.3. 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.

Table B.4. Cumulative Price Response of Soybean Oil to Soybean Price Changes

		τ_O								
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
τ_M 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.

Table C.1. Marginal Effects of Other Factors on Return Coexceedances: Corn and Soybean

	Bottom (5%)		Top (95%)	
	One exceedance	Two exceedances	One exceedance	Two exceedances
Small Shocks				
VIX	-0.015	-0.005	0.012	0.004
	(0.011)	(0.003)	(0.012)	(0.004)
SP500	0.021	0.007	-0.027***	-0.009***
	(0.012)	(0.004)	(0.009)	(0.003)
DXY	-0.011	-0.004	0.057***	0.022***
	(0.01)	(0.003)	(0.013)	(0.006)
News	-0.009	-0.003	0.003	0.001
	(0.011)	(0.003)	(0.011)	(0.004)
EPU	-0.028***	-0.009***	-0.004	-0.001
	(0.009)	(0.003)	(0.011)	(0.004)
CPI	-0.014	-0.005	0.005	0.002
	(0.01)	(0.003)	(0.011)	(0.004)
PPI	0.042***	0.015***	0.039***	0.015***
	(0.013)	(0.005)	(0.013)	(0.005)
Large Shocks				
VIX	0.044***	0.016***	-0.003	-0.001
	(0.014)	(0.006)	(0.013)	(0.005)
SP500	-0.004	-0.001	0.017	0.006
	(0.012)	(0.004)	(0.012)	(0.005)
DXY	0.064***	0.023***	-0.020**	-0.007**
	(0.014)	(0.006)	(0.01)	(0.003)
News	-0.003	-0.001	-0.022**	-0.008**
	(0.011)	(0.003)	(0.009)	(0.003)
EPU	-0.002	-0.001	0.005	0.002
	(0.01)	(0.003)	(0.011)	(0.004)
CPI	0.027**	0.009**	0.018	0.007
	(0.012)	(0.004)	(0.012)	(0.005)
PPI	0.032**	0.011**	0.014	0.005
	(0.013)	(0.005)	(0.012)	(0.005)

Notes: The average marginal effects of other market shocks are reported in the table. These covariates are indicator variables and are divided into two categories. For the category for small (large) shocks, the variable sets to one if its return is below the 5% (95%) tail of the return distribution, and zero otherwise. Standard errors are given in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.2. Marginal Effects of Other Factors on Return Coexceedances: Winter and Spring Wheat

	Bottom (5%)		Top (95%)	
	One exceedance	Two exceedances	One exceedance	Two exceedances
Small Shocks				
VIX	-0.007	-0.006	-0.002	-0.002
	(0.007)	(0.006)	(0.007)	(0.006)
SP500	0.011	0.009	-0.005	-0.004
	(0.008)	(0.007)	(0.007)	(0.006)
DXY	-0.007	-0.006	0.033***	0.031***
	(0.007)	(0.006)	(0.009)	(0.009)
News	-0.011	-0.009	0.006	0.005
	(0.007)	(0.006)	(0.008)	(0.007)
EPU	-0.006	-0.005	-0.004	-0.004
	(0.007)	(0.006)	(0.007)	(0.006)
CPI	0.005	0.004	0.001	0.001
	(0.008)	(0.007)	(0.008)	(0.007)
PPI	0.014*	0.012	0.017**	0.016**
	(0.008)	(0.008)	(0.008)	(0.008)
Large Shocks				
VIX	0.041***	0.037***	0.011	0.010
	(0.011)	(0.011)	(0.009)	(0.009)
SP500	0.000	0.000	0.019**	0.018**
	(0.008)	(0.007)	(0.009)	(0.009)
DXY	0.036***	0.033***	-0.007	-0.006
	(0.009)	(0.009)	(0.007)	(0.006)
News	-0.007	-0.006	-0.008	-0.007
	(0.007)	(0.006)	(0.006)	(0.006)
EPU	-0.011*	-0.009*	0.004	0.004
	(0.006)	(0.005)	(0.007)	(0.006)
CPI	0.028***	0.025***	0.021**	0.020**
	(0.009)	(0.008)	(0.009)	(0.008)
PPI	0.026***	0.023***	0.007	0.006
	(0.009)	(0.008)	(0.008)	(0.007)

Notes: The average marginal effects of other market shocks are reported in the table. These covariates are indicator variables and are divided into two categories. For the category for small (large) shocks, the variable sets to one if its return is below the 5% (95%) tail of the return distribution, and zero otherwise. Standard errors are given in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.3. Marginal Effects of Other Factors on Return Coexceedances: Lean hogs, Live Cattle, Feeder Cattle

	Bottom (5%)			Top (95%)		
	One exceedance	Two exceedances	Three exceedances	One exceedance	Two exceedances	Three exceedances
Small Shocks						
VIX	0.001	0.000	0.000	0.009	0.003	0.000
	(0.013)	(0.005)	(0.001)	(0.013)	(0.004)	(0.001)
SP500	0.008	0.003	0.001	0.001	0.000	0.000
	(0.012)	(0.005)	(0.001)	(0.015)	(0.005)	(0.001)
DXY	0.004	0.002	0.000	0.006	0.002	0.000
	(0.012)	(0.005)	(0.001)	(0.013)	(0.004)	(0.001)
News	0.018	0.007	0.002	-0.012	-0.004	-0.001
	(0.013)	(0.005)	(0.001)	(0.013)	(0.004)	(0.001)
EPU	0.023*	0.009*	0.002*	0.031**	0.010**	0.002*
	(0.012)	(0.005)	(0.001)	(0.014)	(0.005)	(0.001)
CPI	0.032**	0.013**	0.003**	0.027*	0.009*	0.001*
	(0.013)	(0.006)	(0.001)	(0.014)	(0.005)	(0.001)
PPI	0.037***	0.015***	0.003***	0.027*	0.009*	0.001*
	(0.013)	(0.006)	(0.001)	(0.014)	(0.005)	(0.001)
Large shocks						
VIX	0.066***	0.029***	0.006***	-0.028***	-0.008***	-0.001***
	(0.015)	(0.008)	(0.002)	(0.012)	(0.004)	(0.001)
SP500	-0.030***	-0.011***	-0.002***	0.027*	0.009*	0.001*
	(0.01)	(0.004)	(0.001)	(0.014)	(0.005)	(0.001)
DXY	0.02	0.008	0.002	-0.012	-0.004	-0.001
	(0.012)	(0.005)	(0.001)	(0.012)	(0.004)	(0.001)
News	0.040***	0.017***	0.004***	0.040***	0.013***	0.002***
	(0.013)	(0.006)	(0.001)	(0.014)	(0.005)	(0.001)
EPU	0.012	0.005	0.001	0.018	0.006	0.001
	(0.012)	(0.005)	(0.001)	(0.013)	(0.004)	(0.001)
CPI	0.012	0.005	0.001	0.057***	0.019***	0.003***
	(0.013)	(0.005)	(0.001)	(0.015)	(0.006)	(0.001)
PPI	-0.009	-0.003	-0.001	0.010	0.003	0.000
	(0.011)	(0.004)	(0.001)	(0.013)	(0.004)	(0.001)

Notes: The average marginal effects of other market shocks are reported in the table. These covariates are indicator variables and are divided into two categories. For the category for small (large) shocks, the variable sets to one if its return is below the 5% (95%) tail of the return distribution, and zero otherwise. Standard errors are given in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.