Dynamic Linkages in Agricultural and Energy Markets:

A Quantile Impulse Response Approach

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Abstract: This paper investigates the dynamic linkages between agricultural and energy markets, with a focus on an econometric analysis of multivariate stochastic dynamics based on the joint distribution of state variables. The analysis relies on a quantile approach followed by the evaluation of a copula. Applied to nonlinear price dynamics, the approach is flexible and supports a general evaluation of impulse response functions representing how prices adjust over time and across markets in response to a given shock. The analysis allows for arbitrary distribution functions; it captures own-price and cross-price dynamics that can depend on the nature of shocks; and it also allows current changes to affect all moments of the future price distributions. The usefulness of the approach is illustrated in an econometric investigation of dynamic linkages in U.S. corn, ethanol, and crude oil markets. We show how price adjustments can vary across quantiles, reflecting different speeds of adjustments depending on market conditions. We find evidence of nonlinear dynamics specific to the tails of the price distributions. We uncover evidence of positive contemporaneous codependence, especially tail dependence. We show how price shocks affect mean, variance, skewness as well as kurtosis of future price distributions. These results stress the importance of going beyond a standard mean-variance analysis. They also shed new light on the deep linkages existing in the food-fuel nexus.

Keywords: copula, dynamic response, multivariate distribution, prices, quantile.

JEL: C31, C32, G14, Q11

1. Introduction

Evaluating dynamic economic adjustments in agricultural and energy markets has been the subject of much interest[1]. Over the last few decades, the linkages among these markets have been strengthened by U.S. energy and biofuel policy and by the financialization of commodity markets (Hochman et al., 2010; Wright, 2014; Tiwari et al., 2022). Renewed interests in these issues are triggered by the recently expanded Renewable Fuel Standard (i.e., RFS). In March 2023, the U.S. Environmental Protection Agency proposed a new rule that would allow sales of gasoline with a higher ethanol blend in certain U.S. Midwest states, aiming to reduce greenhouse gas emissions. This proposal marks the latest chapter that started with the 2007 RFS policy that required oil refiners to blend billions of gallons of ethanol into the nation's fuel mix. These developments stress the need to understand better the nature and dynamic relationships between agricultural and energy markets so as to inform policymakers as well as refineries, farmers, and investors involved in these markets.

In particular, the large effects arising during recent crises, such as the global financial crisis of 2007-2008, extreme weather, COVID-19 pandemic and geopolitical conflicts, have affected global economic activities and the functioning of commodity markets (e.g., Farid et al., 2022; Cheng et al., 2023). In addition, the financialization of commodity market also played a role in attracting investors into agricultural and energy markets, resulting in increased liquidity and ease of trading (Tang & Xiong, 2012; Bruno et al., 2016). These changes have affected supply and demand conditions as well as prices, leading to an increased likelihood of seeing bearish or bullish markets, rising price volatility and increased risk (especially tail risk). Stronger linkages across markets are also raising new concerns about spillovers of tail risk and their effects on market participants (Wang et al., 2023). As a result, there is a need for a refined analysis of the dynamics of price volatility, with a focus on the impacts of market shocks on skewness and kurtosis of prices in agricultural and energy markets.

However, diverse econometric approaches employed by previous research since the early 2000s, such as vector autoregression (VAR) models, GARCH-type models, wavelets, copula-based methods and their combinations (Janda & Kristoufek, 2019), focusing on mean-variance analysis, failed to examine the dynamics of distributions and their moments' responses to shocks over time. Our analysis is also motivated by several limitations of previous research: 1) previous analyses typically did not allow the speed of dynamic response to depend on the nature of shocks; 2) temporal adjustments often involve nonlinear dynamics; and 3) a focus on mean-variance analysis did not capture the changing nature of tail risk and the dynamic response of higher moments of the price distribution (for example, skewness and kurtosis). Thus, previous research has either ignored or underestimated the likely responses of the price distribution to shocks, especially the evolving nature of tail risk in agricultural and energy markets. This paper fills these gaps by focusing on the evolving nature of price volatility in these markers, with a focus on the role of cross-price effects and the dynamic responses at higher moments to past shocks. While progress has been made in addressing these issues,[2] the so-called "quantile model" provides a flexible approach and is employed widely (Li et al., 2022; Tiwari et al., 2022). In a multivariate setting, this paper goes beyond previous literature by proposing a general quantile approach to the analysis of dynamic moment-based responses, with a focus on evaluating the evolving distribution of prices in agricultural and energy markets.

Our analysis builds on the seminal work of Koenker (2005) and Koenker & Xiao (2004, 2006). Koenker (2005) showed how quantile regression can be used as a flexible method to estimate a distribution function. Koenker & Xiao (2004, 2006) proposed a quantile autoregression (QAR) model to study dynamics. With a focus on multimarket price adjustments, this paper proposes a further extension of this work in a multivariate context: a quantile vector autoregression (QVAR) model. As discussed below, a QVAR approach is flexible in the sense that it allows a price shock to affect the dynamics of the price distribution across markets, thus providing a flexible way to assess the evolution of price volatility in multiple markets. A key challenge is to make a QVAR approach empirically tractable. While progress has been made in this direction,[3] our analysis relies on novel methods that support the estimation of both cross-market dynamics and contemporaneous codependence applied to a multivariate distribution (Li & Chavas, 2023). More importantly, it also allows the assessment of impulse response functions on statistical moments representing the dynamic effects of any shock across markets.[4] By evaluating the dynamics of the joint price distribution, the analysis goes beyond mean-variance analysis and provides useful insights into dynamic price linkages across markets.

Our proposed approach relies on a two-step econometric method. In the first step, specify and estimate a QVAR model representing the dynamic evolution of marginal distribution of each price and capturing both own-price and cross-price dynamic adjustments. In the second step, evaluate a copula representing the joint distribution of prices across all markets, capturing the contemporaneous codependence across markets. The second step builds on Sklar's theorem (Sklar, 1959), showing how a copula provides a formal linkage between marginal distributions and joint distribution (Nelsen, 2006; Joe, 2015). Our proposed two-step method combines these two approaches to support the estimation of the temporal evolution of the joint distribution of prices in multiple markets, with several desirable properties: 1) the analysis applies to arbitrary distribution functions allowing for skewness, nonzero kurtosis and "fat tails"; 2) it allows for dynamics that can depend on the nature of shocks; 3) it provides estimates of the joint distribution that are consistent under general conditions (including non-stationarity and nonlinear dynamics); 4) the proposed econometric approach generates all the information required to evaluate impulse response functions, allowing price responses (both within and across markets) to vary with the nature of the shocks (i.e., to vary across quantiles); 5) the analysis allows for changes that can affect all moments of future prices (including skewness and kurtosis); and 6) the approach supports conducting hypothesis testing.

The usefulness of our proposed approach is illustrated in an evaluation of price dynamics in agricultural and energy markets. Our empirical analysis examines the price dynamics in three U.S. markets (corn, ethanol, and crude oil) over the period 2010-2020. It documents how own-price and cross-price dynamics can vary across quantiles, reflecting different speeds of adjustment depending on market conditions. We find evidence of nonlinear dynamics specific to the tails of the price distributions. Our analysis shows that energy and agricultural markets exhibit positive contemporaneous codependence, especially in tail dependence. We evaluate how initial price changes affect mean, variance, skewness as well as kurtosis of future price distributions. For example, we find that increases in oil prices have significant positive impacts on price kurtosis across markets. The results stress the importance of going beyond a standard mean-variance analysis. They also shed new light on the deep linkages existing between fuel and food markets, information that is valuable for market traders trying to manage their risk exposure in an era of high price volatility.

The paper is organized as follows. In section 2, we provide an overview of the methodological approaches followed in related literature and their main findings. Section 3 presents our two-step econometric approach to the evaluation of dynamic price adjustments in multiple markets. The associated evaluation of dynamic responses is discussed in section 4. Section 5 illustrates the usefulness of our approach in an econometric application to the agricultural and energy markets. The implications of the estimated model for market dynamics are the topics of section 6. Finally, section 7 concludes.

2. Literature Review

Following the introduction of biofuel policy, a growing literature has investigated the dynamic linkages between agricultural and energy markets. For instance, Balcombe & Rapsomanikis (2008), Zhang et al. (2009), Tyner (2010), Pal & Mitra (2017), Chiou-Wei et al. (2019), and Wu et al. (2022) have used multivariate VAR and GARCH models to evaluate the interdependence of prices/returns and volatilities across markets in U.S., Brazil and Europe. Using mean-variance time-series analysis, Du & McPhail (2012) applied dynamic conditional GARCH model and structural VAR model to jointly estimate the contemporaneous evolution of agricultural and energy prices. Variance decomposition showed that corn price changes explain 27% of the variation of ethanol prices, and shocks to ethanol price account for 23% of the variance of corn prices. Using a smooth transition vector error correction model (VECM), Serra et al. (2011) found the causal relationship between ethanol and corn prices but only when the ethanol market is far from the equilibrium regime. Other researchers have also explored patterns of increased volatility and spillovers in fuel-food nexus using MGARCH, GARCH-BEKK and DECO-GARCH models (Abdelradi & Serra, 2015; Saghaian et al., 2018; Herwartz & Saucedo, 2020).

Recent crises along with the growing financialization of commodity markets have also stimulated research examining the nature of tail dependence in crude oil and agricultural markets (Reboredo, 2012; Mensi et al., 2017). Going beyond the mean-variance approaches, copula-based models provide a powerful and suitable framework to investigate these issues (Ghorbel et al., 2017). Indeed, using a copula, bull and bear regimes can be characterized by the time-varying conditional dependence between energy and agricultural commodity markets in a more realistic way. For instance, Kumar et al. (2021) discussed the nature of tail dependence in four distinct regimes: bull and bear oil markets along with bull and bear agricultural markets. Their analysis found evidence of strong co-dependence in the left tail of the price distributions, indicating that the collapse of oil markets and agricultural commodities often happens at the same time during turmoil periods. Along the same lines, Ji et al. (2018) found that lower tail dependence is stronger in a bearish regime than in a bullish one. Hanif et al. (2021) focused on capturing extreme downward movements by using a dependence-switching CoVaR (conditional value-at-risk)-copula model and found significant tail risk spillovers from energy to agricultural commodities. Albulescu et al. (2020) used a copula-based local Kendall's tau approach to measure nonlinear local dependence across regimes in energy and agricultural markets.

Going beyond the empirical contributions just discussed, an important issue is whether food-fuel price transmission across markets is dependent on the nature of the shocks. Using a quantile model, this amounts to examining how dynamic price adjustments and co-dependence vary over quantiles. This can be done by conducting causality-in-quantiles tests, using quantile VAR model, quantile ADL model, quantile coherency approach, or quantile-on-quantile regression (Pal & Mitra, 2017; Khalfaoui et al., 2021; Sun et al., 2023). In general, quantile approaches are more flexible in dealing with extreme values, outliers, and asymmetric distributions with heavy tails as well as other non-normal distributions. Within a causality-in-quantiles framework, Mokni & Ben-Salha (2020) reported that the causal effects of oil prices on food prices appear under almost all market conditions since the 1960s'; they also found evidence that food prices Granger-cause oil prices in the context of bearish and bullish market events. More recently, using a rolling window-based Quantile VAR model, Tiwari et al. (2022) also found significant volatility spillovers from agricultural markets to energy markets during extreme market conditions (i.e., quantile = 0.95). Their findings stress the need to understand better the changing nature of risk spillovers across markets during crisis periods.

As noted above, examining the evolving nature of tail risk requires going beyond a mean-variance analysis. For example, going beyond Markowitz (1952)'s mean-variance approach, it is now well-known that higher moments also play a role in efficient risk management (Jondeau & Rockinger, 2006; Jondeau & Rockinger, 2009; Harvey et al., 2010; Zhang et al., 2023). In addition, there is much interest in evaluating the dynamics of co-movements in price volatility in energy and agricultural markets, with a special focus on studying the time-varying dependence structure and price transmissions across quantiles and across markets. At this point, we note that little is known about the dynamic response of higher moments of prices to shocks. Investigating these issues is a major contribution of this paper. Extending the previous research, this paper develops a novel two-step quantile-based model to explore how food/fuel price shocks affect the mean, variance, skewness, and kurtosis of future price distributions. Applied to agricultural and energy markets, our paper uncovers new and useful evidence on the evolving linkages in these markets.

3. Dynamics: Model and Estimation

Consider prices in n markets $\boldsymbol{p}_t = (p_{1t}, \dots, p_{nt}) \in \mathbb{R}^n$, where p_{it} is the market price at time t in the i-th market, $i \in N \equiv \{1, \dots, n\}$. The price vector $\boldsymbol{p}_t$ evolve over time according to the stochastic difference equation:

$$\boldsymbol{p}_t = \begin{bmatrix} f_1(\boldsymbol{p}_{t-1}, \dots, \boldsymbol{p}_{t-m}, \boldsymbol{x}_t, \boldsymbol{e}_{1t}) \\ \vdots \\ f_n(\boldsymbol{p}_{t-1}, \dots, \boldsymbol{p}_{t-m}, \boldsymbol{x}_t, \boldsymbol{e}_{nt}) \end{bmatrix} \equiv f(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t, \boldsymbol{e}_t), \tag{1}$$

where $m \geq 1$ is the number of lags, $\boldsymbol{P}_{t-1} = (\boldsymbol{p}_{t-1}, \dots, \boldsymbol{p}_{t-m})$, $\boldsymbol{x}_t$ are exogenous shifters and $\boldsymbol{e}_t = (\boldsymbol{e}_{1t}, \dots, \boldsymbol{e}_{nt})$ are random variables representing the effects of unobservable factors. Below, we assume that the random variables $\boldsymbol{e}_t = (\boldsymbol{e}_{1t}, \dots, \boldsymbol{e}_{nt})$ are serially independent with a given joint distribution. Equation (1) is a system of reduced-form equations reflecting the stochastic dynamics of prices $\boldsymbol{p}_t$ in the n markets. Equation (1) as a reduced form model which allows for own price dynamics as well as cross-price dynamics. Note that equation (1) can be associated with a structural model representing the joint determination of prices in the n markets.[5] Our focus on the reduced form model (1) has two advantages: 1) it avoids identification and endogeneity issues arising in structural models; and 2) it can be implemented without requiring information about the behavior of traders in these markets.

In the presence of stochastic terms $\boldsymbol{e}_t = (\boldsymbol{e}_{1t}, \dots, \boldsymbol{e}_{nt})$, the prices $\boldsymbol{p}_t$ in equation (1) can be represented by the joint distribution function:

$$F(\boldsymbol{p}: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t) = Prob\{f_i(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t, \boldsymbol{e}_{it}) \leq p_i, i \in N\}, \qquad (2)$$

where $\boldsymbol{p} = (p_1, \dots, p_n) \in \mathbb{R}^n$. Throughout the paper, we assume that $F(\boldsymbol{p}: \cdot)$ is continuous. Below, we explore the dynamics of prices based on the joint distribution function in equation (2). Of special interest are the dynamic stochastic adjustments taking place both within each market and across markets.

In our econometric analysis, we propose to rely on a two-step approach. In the first step, consider evaluating the marginal distribution associated with price in the i-th market:

$$F_i(p_i: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t) = Prob\{f_i(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t, \boldsymbol{e}_{it}) \leq p_i\}, \qquad (3a)$$

$p_i \in \mathbb{R}, i \in N$. The terms $\boldsymbol{P}_{t-1} = (\boldsymbol{p}_{t-1}, \dots, \boldsymbol{p}_{t-m})$ in (3a) reflect price dynamics across all markets (including both own price dynamics captured by $p_{i,t-k}$ and cross price dynamics captured by $p_{j,t-k}, j \neq i$) and their effects on the marginal distribution $F_i, i \in N$.

In the second step, using Sklar's theorem (Sklar, 1959), consider the general relationship existing between the joint distribution in equation (2) and the marginal distributions in equation (3a):

$$F(\boldsymbol{p}: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t) = C[F_1(\boldsymbol{p}: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t), \dots, F_n(\boldsymbol{p}: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t)], \qquad (3b)$$

where $C(F_1, \dots, F_n): [0,1]^n \to [0,1]$ is a copula (Sklar, 1959; Nelsen, 2006). The copula in equation (3b) applies to any distribution and captures the contemporaneous codependence among prices $\boldsymbol{p}_t = (p_{1t}, \dots, p_{nt})$.[6] Equation (3b) makes it clear that evaluating the marginal distributions $F_i(p_i: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t)$ in the first step, and then combining them using the copula $C(F_1, \dots, F_n)$ in the second step provide all the information about the joint distribution $F(\boldsymbol{p}: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t)$. In turn, knowing this joint distribution provides all the information needed to evaluate the stochastic dynamics of $\boldsymbol{p}_t = (p_{1t}, \ldots, p_{nt})$. Below, we discuss our proposed two-step econometric approach, its flexibility, its statistical properties, and its empirical tractability.

The first step involves the specifying and estimating the marginal distribution function $F_i(p_i: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t), i \in N$. It would be convenient for us to focus on the associated quantile function defined as the inverse of $F_i(p_i: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t)$:

$$Q_i(q_i: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t) \equiv \inf_{p_i} \{p_i: F_i(p_i: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t) \geq q_i\}, \tag{4}$$

where $q_i \in [0, 1]$ denotes the q_i-th quantile of p_{it}, $i \in N$. Below, we consider the following model specification for the quantile function (4):

$$Q_i(q_i: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t, \theta_i(q_i)) = \alpha_i(q_i) + \sum_{j=1}^{m} \sum_{k=1}^{n} \beta_{ijk}(q_i)\, p_{k,t-j} + \gamma_i(q_i)\, x_t$$

$$+\eta_i(q_i)\, g_i(\boldsymbol{P}_{t-1}), \tag{5}$$

where $q_i \in [0, 1]$ is the q_i-th quantile, $\theta_i = (\alpha_i, \beta_i, \gamma_i, \eta_i)$ are parameters to be estimated and $g_i(\boldsymbol{P}_{t-1})$ is a nonlinear function of $\boldsymbol{P}_{t-1}$ capturing the presence of nonlinear dynamics (as further discussed in section 4.2), $i \in N$. Equation (5) is a quantile vector autoregression (QVAR) that provides a flexible representation of price dynamics. It is a multivariate extension of the quantile autoregression (QAR) model proposed by Koenker (2005) and Koenker and Xiao (2006). The specification (5) has several desirable characteristics. First, when the parameters $(\beta_{ijk}(q_i), \gamma_i(q_i), \eta_i(q_i))$ are constant across all quantiles and $\alpha_i(q_i) = \alpha_i + v_i$ where v_i is a random variable with mean 0, then equation (5) reduces to a standard vector autoregression (VAR) model commonly found in the time series literature (e.g., Hamilton, 1994; Enders, 2010). Second, allowing the parameters $\alpha_i(q_i)$'s to vary across quantiles means that (5) can represent arbitrary marginal distribution functions for p_i, including non-symmetric and fat-tailed distributions. Third, the QVAR model (5) allows for own-price dynamics (as captured by $\beta_{iik}(q_i)$) as well as cross-market dynamics (as captured by $\beta_{ijk}(q_i), j \neq i$). Fourth, when the parameters $\beta_{ijk}(q_i)$'s vary across quantiles, then market shocks (represented by q_i) affect price adjustments and the dynamics of the whole price distribution (including mean, variance, skewness, and higher moments). Finally, when $\eta_i(q_i) \neq 0$, $g_i(\boldsymbol{P}_{t-1})$ being a nonlinear function of $\boldsymbol{P}_{t-1}$ means that (5) allows for nonlinear dynamics.

Importantly, equation (5) provides a basis to evaluate the nature of price dynamics. Under differentiability, let $a_{ijk}(q_i, \boldsymbol{P}_{t-1}, \theta_i) \equiv \partial Q_i(q_i\colon \boldsymbol{P}_{t-1}, \boldsymbol{x}_t, \theta_i)/\partial p_{k,t-j}$. Evaluated at point $\boldsymbol{P}_{t-1}$, consider the first-order Taylor series approximation of (5): $Q_i(q_i\colon \boldsymbol{P}_{t-1}, \boldsymbol{x}_t, \theta_i) \approx a_i(q_i, \boldsymbol{P}_{t-1}, x_t, \theta_i) + \sum_{j=1}^{m} \sum_{k=1}^{n} a_{ijk}(q_i, \boldsymbol{P}_{t-1}, \theta_i)\, p_{k,t-j}$. This is a set of linear difference equation of order $(n\, m)$ providing information about local dynamics in the neighborhood of point $(\boldsymbol{q}, \boldsymbol{P}_{t-1})$, where quantile $\boldsymbol{q} = (q_1, \dots, q_n)$. This set of linear difference equation has $(n\, m)$ roots: $\lambda_1(\boldsymbol{q}, \boldsymbol{P}_{t-1}), \dots, \lambda_{nm}(\boldsymbol{q}, \boldsymbol{P}_{t-1})$. Ordering the roots according to their modulus, we have $|\lambda_1(\boldsymbol{q}, \boldsymbol{P}_{t-1})| \geq |\lambda_2(\boldsymbol{q}, \boldsymbol{P}_{t-1})| \geq \cdots \geq |\lambda_{nm}(\boldsymbol{q}, \boldsymbol{P}_{t-1})|$ where $\lambda_1(\boldsymbol{q}, \boldsymbol{P}_{t-1})$ is the dominant root. Then, in the neighborhood of $(\boldsymbol{q}, \boldsymbol{P}_{t-1})$, $log|\lambda_1(\boldsymbol{q}, \boldsymbol{P}_{t-1})|$ measures the rate of divergence in prices $\boldsymbol{p}_t$ along a forward trajectory (Hasselblatt & Katok, 2003, p. 19-21). In standard VAR models (where $\eta_i(q_i) = 0$ and $\beta_{ijk}(q_i)$ are the same and fixed across all quantiles), $\lambda_1(\boldsymbol{q}, \boldsymbol{P}_{t-1})$ would become independent of $(\boldsymbol{q}, \boldsymbol{P}_{t-1})$, yielding the standard result that $|\lambda_1| < 1$ corresponds to global dynamic stability (e.g., Hamilton, 1994, p. 259). In the QVAR model (5), this result still applies but only locally: when evaluated at point $(\boldsymbol{q}, \boldsymbol{P}_{t-1})$, log $(|\lambda_1(\boldsymbol{q}, \boldsymbol{P}_{t-1})|)$ measures the local rate of divergence of prices $\boldsymbol{p}_t$ along a forward trajectory. In this context, equation (5) would exhibit local dynamic stability at point $(\boldsymbol{q}, \boldsymbol{P}_{t-1})$ if $|\lambda_1(\boldsymbol{q}, \boldsymbol{P}_{t-1})| < 1$.

Alternatively, having $|\lambda_1(\boldsymbol{q}, \boldsymbol{P}_{t-1})| > 1$ would imply that, at point $(\boldsymbol{q}, \boldsymbol{P}_{t-1})$, prices $\boldsymbol{p}_t$ would diverge at a rate equal to $\log(|\lambda_1(\boldsymbol{q}, \boldsymbol{P}_{t-1})|)$. When the parameters $\beta_{ijk}(q_i)$ and $\eta_i(q_i)$ change across quantiles, $\lambda_1(\boldsymbol{q}, \boldsymbol{P}_{t-1})$ would also change with $\boldsymbol{q}$, making it clear that equation (5) allows for price dynamics to vary across quantiles. To the extent that different quantiles $\boldsymbol{q} = (q_1, \ldots, q_n)$ reflect different contemporaneous shocks, this indicates that the quantile model (5) allows for price dynamics to vary with market conditions in each of the n markets. Finally, when $\eta_i(q_i) \neq 0$, there is nonlinear dynamics which means that $\lambda_1(\boldsymbol{q}, \boldsymbol{P}_{t-1})$ depends on past prices $\boldsymbol{P}_{t-1}$; and when $\eta_i(q_i)$ varies with q_i, equation (5) allows nonlinear dynamics to vary across quantiles. Note that such properties are not exhibited in VAR models, indicating that VAR models do not provide a flexible representation of dynamic response to price shocks. This is an argument in favor of model (5) and its use in the evaluation of dynamic response functions.

Besides providing a flexible representation of the evolving marginal quantiles/distributions of prices $(p_{1t}, \ldots, p_{nt})$, the QVAR model (5) can be easily estimated as a quantile regression model (Koenker, 2005; Koenker & Xiao, 2006). Consider a sample of τ observations $\{(\boldsymbol{p}_t, \boldsymbol{P}_{t-1}, \boldsymbol{x}_t): t \in T\}$ where $T = \{1, \ldots, \tau)$. For a given quantile $q_i \in [0, 1]$, the quantile estimator of the parameters in equation (5) is:

$$\theta_i^e(q_i) \in argmin_{\theta_i} \{\textstyle\sum_{t \in T} \rho_\tau(p_{it} - Q_i(q_i: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t, \theta_i)\}, \qquad (6)$$

where $\rho_\tau(w) = w\,[\tau - I(w < 0)]$ and $I(\cdot)$ is the indicator function, $i \in N$. Under some regularity conditions, the quantile estimator in (6) is consistent, with $\theta_i^e(q_i) \xrightarrow{d} \theta_i(q_i), i \in N$ (Koenker, 2005; Koenker & Xiao, 2006; Angrist et al., 2006; White et al., 2015). As showed by Koenker & Xiao (2004), the consistency property also holds under a unit root process, but the asymptotic distribution of the estimators depends on the properties of the stochastic model. This is relevant in the context of conducting hypothesis. To deal with this issue, following Efron & Tibshirani (1994), Koenker & Xiao (2004), Koenker (2005, p. 107) and Chernozhukov et al. (2013), we rely on the bootstrap method in hypothesis testing.

In the second step, the consistent estimator $\theta_i^e(q_i)$ in (6) can be used to estimate the copula $C(F_1, \dots, F_n)$ in (3b). Let $Q_{it}^e(q_i) \equiv Q_i\big(q_i: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t, \theta_i^e(q_i)\big)$ be a consistent predictor of $Q_i(q_i: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t, \theta(q_i), i \in N$ (Chernozhukov et al., 2013). Under the absolute continuity of the distribution function, we have $q_i = F_i(Q_i(q_i: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t): \boldsymbol{P}_{t-1}, \boldsymbol{x}_t)$. For each $i \in N$ and $t \in T$, solve the equation $p_{it} = Q_{it}^e(q_i)$ for q_i, yielding q_{it}^e. Noting that the consistency property is maintained under continuous transformations (Hayashi, 2000, p. 92), it follows that q_{it}^e provides a consistent estimate of $F_i(p_{it}: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t)$ that can be used in the estimation of the copulas $C(F_1, \dots, F_n)$ in (3b). Copulas can be estimated using either parametric methods or nonparametric methods (Nelsen, 2006; Joe, 2015). For example, a nonparametric estimator is given by the empirical distribution function $C^e(\boldsymbol{q}) = [\sum_{t \in T} I(q_{1t}^e \leq q_1, \dots, q_{nt}^e \leq q_n]/\tau$, where $\boldsymbol{q} = (q_1, \dots, q_n)$. In general, the empirical distribution is a consistent estimator of the underlying distribution function (van der Vaart, 1998, p. 281). It follows that $C^e(\boldsymbol{q})$ is a consistent estimator of $C(\boldsymbol{q})$, with $C^e(\boldsymbol{q}) \xrightarrow{d} C(\boldsymbol{q})$. But the asymptotic distribution of the second-step estimator depends on the statistical properties of the first-step estimator (Murphy & Topel, 2002; Wooldridge, 2010). To address this issue, hypothesis testing related to second-step estimates can be conducted using the bootstrap method applied over both steps of the estimation approach (Wooldridge, 2010; Chernozhukov et al., 2013).

As noted above, the copula $C(\boldsymbol{q})$ provides a general representation of contemporaneous codependence across all n markets. When $n > 2$, it would be convenient to focus our attention on bivariate copulas, the codependence analysis being conducted two markets at a time. For some $k \in N$ and $i \in N - k$, the following general relationship holds between the bivariate copula $C_{ik}(q_i, q_k)$ and the joint copula $C(\boldsymbol{q})$: $C_{ik}(q_i, q_k) \equiv C(\delta_{1ki}, \delta_{2ki} \dots, \delta_{nki})$ where $\delta_{jik} = \begin{Bmatrix} q_i \\ q_k \\ 1 \end{Bmatrix}$ if $\begin{Bmatrix} j = i \\ j = k \\ j \in N - i - k \end{Bmatrix}$. It means that $C_{ik}^e(q_i, q_k)$ can be obtained from $C^e(\boldsymbol{q})$. As discussed below, it would be useful to consider the associated conditional distribution function $C_{i|k}(q_i|q_k)$,

$$C_{i|k}(q_i|q_k) \equiv Prob[U_i \leq q_i : U_k = q_k]$$

$$= \lim_{\delta \to 0} \frac{C_{ik}(q_i, q_k + \delta) - C_{ik}(q_i, q_k)}{\delta} = \frac{\partial C_{ik}(q_i, q_k)}{\partial q_k}, \tag{7}$$

where $U_j \sim U[0,1], j \in N$ (Nelsen, 2006, p. 41; Joe, 2015, p. 30). The conditional distribution $C_{i|k}(q_i|q_k)$ captures the contemporaneous codependence between markets i and k, codependence that can vary across quantiles (q_i, q_k). Using the consistent estimates (q_i^e, q_k^e) and equation (7), the conditional distribution $C_{i|k}(q_i|q_k)$ can be estimated directly: it can be parametrized and its parameter estimated by quantile regression, yielding an estimate $C_{i|k}^e(q_i|q_k)$.[7] To illustrate, in section 4 below, we consider the following specification:

$$C_{i|k}(q_i, q_k) = c_{0k}(q_i) + c_{1k}(q_i)\, q_k, \tag{8}$$

where the parameters $(c_{0k}(q_i), c_{1k}(q_i))$ are quantile regression parameters under quantile $q_i \in [0,1]$.[8] In equation (8), prices (p_i, p_k) would exhibit contemporaneous independence when $c_{0k}(q_i) = q_i$ and $c_{1k}(q_i) = 0$ for all $q_i \in [0,1]$. Alternatively, having $c_{1k}(q_i) >$

0 (< 0) would correspond to q_k having positive (negative) codependent effects on quantile $q_i \in [0, 1]$. The estimates $C^e_{i|k}(q_i|q_k)$ are used in our analysis, as discussed next.

4. Evaluating Dynamic Responses

The previous section has described a two-step method to estimate the dynamics of the joint distribution of n prices $\boldsymbol{p} = (p_1, \dots, p_n)$ at time $t \in T$, as given by $F(\boldsymbol{p}: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t)$: price dynamics can be evaluated based on the QVAR model (5); and the contemporaneous codependence across markets can be evaluated based on the copula $C(\boldsymbol{q})$. This section proposes a method to evaluate the nature of dynamic price adjustments across the n markets.

Our proposed evaluation of the dynamic paths of prices $\boldsymbol{p}_t$ relies on a forward simulation of the evolving distribution $F(\boldsymbol{p}: \boldsymbol{P}_{t-1}, \boldsymbol{x}_t)$ over TT periods under alternative scenarios. Let the s-th scenario correspond to a given initial conditions $\boldsymbol{P}_{0s}$ and holding constant the explanatory variables in the forward path: $\boldsymbol{x}_t = \boldsymbol{x}_{0s}, t = 1, \dots, TT$. For the s-th scenario, we propose conducting a stochastic simulation over D forward paths. The simulation scheme is as follows. Start with $t = 1$, $d = 1$ and $\boldsymbol{P}_{1,t-1} = \boldsymbol{P}_{0s}$.

Step 1: For some $k \in N$, get a random draw q_{kdt} from a uniform distribution $U[0, 1]$ and obtain $Q^e_{kdt} = Q_k\left(q_{kdt}: \boldsymbol{P}_{d,t-1}, \boldsymbol{x}_{0s}, \theta^e_k(q_{kdt})\right)$.

Step 2: For each $i \in N - k$, obtain $q_{idt} = C^e_{i|k}(v_{idt}|q_{kdt})$ where v_{idt} is a random draw from $U[0, 1]$, and obtain $Q^e_{idt} = Q_i\left(q_{idt}: \boldsymbol{P}_{d,t-1}, \boldsymbol{x}_{0s}, \theta^e_i(q_{idt})\right)$.

Step 3:

3a: If $d < D$, let $d = d + 1$ and go to step 1.

3b: If $d = D$ and $t < TT$, update $\boldsymbol{P}_{d,t}$ by replacing prices in period t by $(Q_{1dt}^e, \dots, Q_{ndt}^e)$ for all d; then let $t = t + 1$ and go to step 1.

3c: If $d = D$ and $t = TT$, then stop.

Conditional on $\boldsymbol{P}_{0s}$, the above scheme generates D forward price paths on n prices over TT periods. This includes D simulated prices $Q_{it}^e(\boldsymbol{P}_{0s}) = \{Q_{idt}^e : d = 1, \dots, D\}$ representing the distribution of the i-th price at the forward period t. This information can be used to evaluate the moments of each price along its forward path. Assuming that they are finite, these moments include the mean:

$$M_{1it}^e(\boldsymbol{P}_{0s}) = E[Q_{it}^e(\boldsymbol{P}_{0s})], \tag{9a}$$

and the j-th central moment:

$$M_{jit}^e(\boldsymbol{P}_{0s}) = E[[Q_{it}^e(\boldsymbol{P}_{0s}) - M_{1It}^e]^j], \tag{9b}$$

$j = 2, 3, 4, \dots$, where E is the expectation operator, $i \in N$ and $t = 1, \dots, TT$. Depending on the value of j, equation (9b) gives estimates of the variance $M_{2it}^e(\boldsymbol{P}_{0s})$, the standard deviation $[M_{2it}^e(\boldsymbol{P}_{0s})]^{0.5}$, the skewness $\frac{M_{3it}^e(\boldsymbol{P}_{0s})}{[M_{2it}^e(\boldsymbol{P}_{0s})]^{1.5}}$, as well as the kurtosis $\left[\frac{M_{4it}^e(\boldsymbol{P}_{0s})}{[M_{2it}^e(\boldsymbol{P}_{0s})]^2} - 3\right]$. While skewness and kurtosis are equal to 0 under a normal distribution, a non-zero skewness reflects an asymmetric probability function, and a positive kurtosis arises when the probability function exhibits "thick tails".

This scheme can be repeated after changing the initial conditions from $\boldsymbol{P}_{0s}$ to $\boldsymbol{P}_{0s'}$ generating estimates of how the forward path of the price distributions changes with the initial conditions. Using (9a), this includes $[M_{1it}^e(\boldsymbol{P}_{0s'}) - M_{1it}^e(\boldsymbol{P}_{0s})]$ as estimate of the effect of a change from $\boldsymbol{P}_{0s}$ to $\boldsymbol{P}_{0s'}$ on the mean path of price p_i after t periods, $t \in \{1, \dots, TT\}$. And using (9b), this also includes $[M_{jit}^e(\boldsymbol{P}_{0s'}) - M_{jit}^e(\boldsymbol{P}_{0s})], j = 2,3,4, \dots$ as estimate of the effect of a change from $\boldsymbol{P}_{0s}$ to $\boldsymbol{P}_{0s'}$ on the path of the j-th central moment of the price p_i after t periods. When the change from $\boldsymbol{P}_{0s}$ to $\boldsymbol{P}_{0s'}$ involves a change in a single price (say price p_k), this scheme generates estimates of dynamic multipliers measuring the effects of a change in p_k on the path of all future prices. Interpreting these dynamic multipliers as impulse response functions, the above scheme provides a general way to estimate impulse response functions.[9]

This scheme depends on the quantile estimates of θ^e given in equation (6). As noted above, the consistency property of θ^e being preserved under continuous transformations, it follows that, when finite, the estimated moments given in (9a)-(9b) are also consistently estimated. In addition, following Efron & Tibshirani (1994), their distribution can be obtained by bootstrapping as follows: 1) after resampling (with replacement) from the data, obtain new estimates of θ^e; 2) use these estimates to obtain new estimates of the simulated moments in (9a)-(9b); 3) repeat this process many times to obtain an estimate of the distribution of $M^e_{jit}(\boldsymbol{P}_{0s'}) - M^e_{jit}(\boldsymbol{P}_{0s}), j = 1, 2, \ldots$. This process can be used to evaluate the distribution of the dynamic effects of $\boldsymbol{P}_{0s}$ on the moments of future prices. This is illustrated next in an application.

5. An application to agricultural and energy markets

The usefulness of the approach discussed in sections 3-4 is illustrated in an application to U.S. food and fuel markets. The econometric application focuses on three commodities: corn, ethanol, and crude oil. The dynamic linkages between prices in these three markets have been of considerable interest. In the U.S., the introduction of the Energy Policy Act in 2005, the passage of the Energy Independence and Security Act of 2007, and the final rules of 2023-2025 RFS, have stimulated the use of ethanol (produced using corn) as a (partial) substitute for gasoline and contributed to the increase in corn ethanol production from 3.904 billion gallons in 2005, to 13.298 billion in 2010, and to 20.101 billion in the first 11 months of 2023.[10] More than four-fifths of U.S. biofuel production capacity was for corn ethanol.[11] The growing importance of corn ethanol in the U.S. has strengthened the linkages between agricultural and energy markets in two important ways: 1) by reducing the demand for oil used in the production of gasoline; and 2) by increasing land allocation away from food production toward biofuel production, thus stimulating a debate about the changing role of agriculture (Ciaian & Kancs, 2011; Zilberman et al., 2012). These ongoing implementation and expansion of RFS programs have also raised questions about the nature of dynamic adjustments in the food and fuel markets. Our analysis provides new evidence on these issues.

5.1. Data

Weekly nearby prices of the No.2 Yellow Corn futures contracts are obtained from the Chicago Board of Trade (CBOT). Weekly ethanol and crude oil futures are denatured fuel ethanol for blending with gasoline and West Texas Intermediate (WTI) crude oil from the New York Mercantile Exchange (NYMEX), respectively. Futures prices are rolled into the next nearby contracts on the first Wednesday of the delivery month, collected from the data source of Barchart. The sample period considered runs from January 2010 to October 2020, resulting in 557 weekly observations.[12] In our empirical analysis, prices are measured as $log(price)$, implying that their corresponding coefficients can be interpreted as elasticities.

[PLEASE INSERT FIGURE 1 HERE]

Figure 1 reports the trajectories of weekly corn, ethanol, and crude oil prices over the last decade. All three prices experienced dramatic rises and falls during the sample period. Price movements in the three markets tend to be highly correlated, with higher prices before 2014 and dramatic declines in early 2020. The crude oil prices were fairly stable and relatively high before September 2014, and then fell sharply and became more volatile in part due to the shale revolution in North America. While similar price patterns are observed in ethanol and corn markets during the same timeframe, the declines were of smaller magnitudes than for crude oil. More recently, the coronavirus pandemic had a large impact on global economic activities, including the energy and agricultural markets. The price of WTI crude oil declined sharply in April 2020. The historical lowest price of ethanol and the large decline in corn prices are also observed in early 2020.

[PLEASE INSERT TABLE 1 HERE]

Table 1 presents summary statistics for the log of price index in each market (with each price index set to be equal to 100 on January 6, 2000). Several patterns emerge from the reported statistics. First, crude oil prices tend to be more volatile than ethanol or corn prices. Second, each of the three prices appears to have a skewed distribution. And the excess kurtosis for crude oil is positive and statistically significant. Based on the Jarque-Bera test, the normality assumption is rejected for all three price series. The evolving relationship between food and fuel prices is examined next.

5.2. Econometric Specification

We employ the two-step econometric approach discussed in sections 3-4 (relying on QVAR and copula) and apply it to investigate the dynamics linkages between U.S. corn, ethanol, and crude oil prices. The QVAR model discussed in Equation (5) provides a good basis to analyze the evolution of the distribution of food-fuel prices. Going beyond previous research, our QVAR model allows for linear and nonlinear dynamics with price adjustments varying across quantiles. Nonlinear dynamics is captured by the nonlinear function $g_i(\boldsymbol{P}_{t-1})$ in equation (5). Below, we measure such nonlinearities using squared deviations from sample median, with $g_i(\boldsymbol{P}_{t-1}) = \{p^s_{i,t-1}: i \in (c, e, o)\}$, where $p^s_{i,1} \equiv \left(p_{i,t-1} - Mp_i\right)^2$ and Mp_i is the sample median for p_i.

The first question to address is the specification for the QVAR model (5). We explored alternative model specifications for (5), including the number of lags m, the explanatory variables $\boldsymbol{x}_t$ (including trend and seasonality), and the choice of $g(\boldsymbol{Y}_{t-1})$ reflecting nonlinear dynamics. The fit of these alternative specifications was evaluated using the Bayesian Information Criterion (BIC) (Schwarz, 1978). We estimated many QVAR models for each commodity price, each involving lagged price effects, time trend[13] and seasonality, nonlinear dynamics, and quantile effects. All models include lagged corn, ethanol, and crude oil prices, with the number of lags between 1 and 4. Seasonality is captured using sine and cosine terms (sin, cos), monthly dummies, and/or quarterly dummies.

Using the BIC Criterion, alternative model specifications were evaluated across quantiles.[14] Our choice of model specification was done for three quantile categories: lower, middle, and upper quantiles. On that basis, we proceed with our analysis with specific models across quantiles, using BIC as a guide to identify which QVAR models provide a good representation of dynamics of the distribution for three commodities. To illustrate, using BIC, we found that seasonality plays an important role but only in the corn market (and not in the crude oil or ethanol market), likely reflecting the seasonality of corn production. In addition, seasonal patterns for corn were found to be important only in the upper and lower quantiles.

5.3. Estimates of marginal distributions

Guided by the BIC, we specified and estimated the QVAR model in (5) for the marginal price distributions. Tables 2-4 report the QVAR estimates for corn, ethanol, and crude oil under selected quantiles: $q = (0.1, 0.2, \dots, 0.8, 0.9)$, with standard errors obtained using bootstrapping.[15] Our QVAR models have good explanatory power: the pseudo-R^2 proposed by Koenker & Machado (1999) varies between 0.788 and 0.900. First, consistent with previous research, we find evidence of seasonality and time trend tt in the corn market, effects which are statistically significant in most quantiles. Second, the effects of lagged prices are statistically significant in each of the three equations, documenting the importance of dynamic adjustments in the price distributions. Tables 2-4 show that the own lagged price coefficients differ across commodities and across quantiles.[16] From Table 2 for corn, the coefficient of $p_{c,t-1}$ is around 1 around the median; but it declines slightly in the tails of the distribution. For ethanol, Table 3 reports that the coefficient of $p_{e,t-1}$ is lowest in the lower quantiles, but it tends to increase toward 1 in the upper quantiles. The estimates differ for oil: Table 4 shows that the coefficient of $p_{o,t-1}$ is highest (and above 1) in the lower quantiles, but it declines below 1 around the median and in the upper quantiles. These results have three implications: 1) the patterns of dynamic price adjustments differ across markets; 2) responses vary depending on the nature of the shocks: positive shocks in the upper tail of the distribution can have different effects compared to negative shocks in the lower tail of the distribution (note that this result stresses the usefulness of our QAR approach); and 3) the estimates reported in Table 4 suggest that there may be some overreaction to negative shocks in the dynamics of oil price (as further discussed below).

[PLEASE INSERT TABLE 2 HERE]

Third, Tables 2-4 also report dynamic cross-price effects. For corn in Table 2, lagged ethanol price does not have statistically significant effects, but lagged oil price has a positive and statistically significant effect on $p_{c,t}$ in the lower quantiles where $q_c \leq 0.2$. For ethanol, Table 3 reports strong cross-price effects with both corn and oil, reflecting that corn is a key input in the production of ethanol and that ethanol is a substitute source of energy; but these effects vary across quantiles. The lagged price of corn has positive and statistically significant effects on $p_{e,t}$ below the median (where $q_e \leq 0.5$). The lagged prices of oil have statistically significant effects on $p_{e,t}$ below the median (where $q_e \leq 0.5$), with effects that are positive for $p_{o,t-1}$ but negative for $p_{o,t-2}$. This indicates that cross-price effects differ in the short term versus the intermediate term. In addition, the effect of $p_{o,t-1}$ on $p_{e,t}$ is also found to be positive and significant at quantile $q_e = 0.7$. These estimates stress the importance of allowing for dynamic effects to vary across quantiles, with ethanol prices being highly affected by corn and oil prices, especially under bearish market conditions. For oil, Table 4 shows that lagged prices of corn have statistically significant effects on $p_{o,t}$ at quantile $q_o = 0.1$, with effects that are positive for $p_{c,t-1}$ but negative for $p_{c,t-2}$; and $p_{c,t-1}$ has also positive and significant effect on $p_{o,t}$ at quantile $q_o = 0.9$. And the lagged price of ethanol has some positive effects on $p_{o,t}$ at quantiles $q_o = 0.1$ and 0.6, reflecting some substitution relationships. Thus, in a way different with Vo et al., (2019) and Vu et al. (2019), the relationship between oil price and food price does not go only from oil price to food price. Our finding partially supports the work of Mokni & Ben-Salha (2020) who also showed a significant causality running from food to oil prices, generally at extreme markets conditions (in low and high quantiles).

[PLEASE INSERT TABLE 3 HERE]

Finally, Tables 2-4 report nonlinear dynamic effects captured by the terms $p_{i,t-1}^{s}$, measuring the squared deviation of $p_{i,t-1}$ from sample median. We find that the effects of $p_{c,t-1}^{s}$ on $p_{c,t}$ and of $p_{o,t-1}^{s}$ on $p_{e,t}$ and $p_{o,t}$ are statistically significant in the low or high quantiles. Thus, we uncover evidence that nonlinear dynamics occur in the tail of the agricultural and energy price distributions. This is consistent with nonlinear asymmetric adjustment processes in the food and fuel markets (Cheng & Cao, 2019; Rafiq & Bloch, 2016; Serra et al., 2011). These nonlinearities differ across commodities. For both corn and ethanol, nonlinear dynamic effects are found to be positive and statistically significant in the tails of the price distribution. Given $p_{i,t-1}^{s} \equiv \left(p_{i,t-1} - Mp_i\right)^2$, note that $p_{i,t-1}^{s}$ is a decreasing (increasing) function of $p_{i,t-1}$ when $p_{i,t-1}$ is below (above) the corresponding median price. For corn in Table 2, the positive effects of $p_{c,t-1}^{s}$ mean that $p_{c,t-1}$ has weaker (stronger) effects on $p_{c,t}$ when the lagged corn price is below (above) the median <u>and</u> in the presence of negative shocks (i.e., in the lower tail of the corn price distribution with $q_c \leq 0.3$). For ethanol in Table 3, the positive effects of $p_{o,t-1}^{s}$ mean that $p_{o,t-1}$ has weaker (stronger) effects on $p_{e,t}$ when the lagged oil price is below (above) the median <u>and</u> in the presence of positive shocks (i.e., in the upper tail of the ethanol price distribution when $q_e \geq 0.6$). Importantly, the nonlinear dynamics differ for oil. Table 4 shows that $p_{o,1}^{s}$ has positive effects on $p_{o,t}$ in the upper tail ($q_o \geq 0.7$) but negative effects in the lower tail ($q_o = 0.1$). This means that lagged price $p_{o,t-1}$ has stronger effects on $p_{o,t}$ when the lagged oil price is above the median <u>and</u> in the presence of positive shocks in the oil market;

and $p_{o,t-1}$ has stronger effects on $p_{o,t}$ when the lagged oil price is below the median and in the presence of negative shocks in the oil market. Under this last scenario, nonlinear dynamics contribute to stimulating dynamic adjustments in the oil market under the joint presence of low-lagged oil price and negative shocks. As further discussed below, this is a situation that can contribute to local instability.

[PLEASE INSERT TABLE 4 HERE]

5.4. Estimates of joint distributions

Having estimated the marginal distributions, we proceed with evaluating the joint distribution. We start with evaluating the conditional distribution $C_{i|k}(q_i|q_k)$ given in equations (7)-(8). Conditional on the crude oil price, the quantile estimates of $C_{c|o}(q_c|q_o)$ for corn and $C_{e|o}(q_e|q_o)$ for ethanol are reported in Table 5 for selected quantiles.[17] Relying on bootstrapping, we conducted formal tests on the estimates, documenting that the term q_o has a statistically significant effect and is consistently positive across all quantiles in both the corn and ethanol equations. The coefficient of q_o varies from 0.081 at $q_c = 0.1$ to 0.286 at $q_c = 0.6$ in the corn equation; and it is in the range between 0.104 at $q_e = 0.1$ and 0.386 at $q_c = 0.7$ in the ethanol equation. These results indicate the presence of stronger contemporaneous codependence between ethanol and oil than between corn and oil.

[PLEASE INSERT TABLE 5 HERE]

Also, using bootstrapping, we formally tested whether the parameter estimates vary across quantiles. As reported in Table 5, for both corn and ethanol, the test results find strong statistical evidence that the coefficient of q_o varies significantly across quantiles, with effects that tend to be stronger in the upper tail of the price distributions. Thus, contemporaneous shocks in the oil price are of crucial importance as they affect both corn and ethanol prices, reflecting strong linkages in food-fuel nexus.

6. Implications for Dynamics

6.1. Dynamic Stability

As discussed in section 2, the nature of price dynamics across our three markets can be evaluated using the roots of a linearized version of the estimated QAR model given in (5). The model being nonlinear in P_{t-1}, these roots depend on lagged prices; and they vary across quantiles. The modulus of the dominant root $|\lambda_1(\boldsymbol{q}, \boldsymbol{P}_{t-1})|$ is reported in Table 6 for selected quantiles $\boldsymbol{q} = (q_c, q_e, q_o) \in [0, 1]^3$ with $\boldsymbol{P}_{t-1}$ evaluated at median prices. An evaluation of the role of nonlinear dynamics and the effects of $\boldsymbol{P}_{t-1}$ on $|\lambda_1(\boldsymbol{q}, \boldsymbol{P}_{t-1})|$ is presented in Appendix C. Recall that $|\lambda_1| < 1$ (> 1) corresponds to local stability (local instability). Finding that the dominant root $|\lambda_1(\boldsymbol{q}, \boldsymbol{P}_{t-1})|$ varies across quantiles implies that local stability varies with market conditions. Table 6 shows that the dominant root $|\lambda_1|$ is significantly greater than 1 in the lower tail of the oil price distribution (i.e., $q_0 = 0.1$); it also reports that $|\lambda_1|$ declines with q_o and becomes near or less than 1 where $q_0 \geq 0.3$ for all (q_c, q_e). These are important results. First, the food-fuel markets are found to exhibit local stability when $q_0 \geq 0.3$. Second, we find evidence that these markets become locally unstable in the presence of extreme negative shocks in the oil market (when $q_o = 0.1$). Finally, as showed in Appendix C (in Tables C1 and C2), these qualitative results remain broadly valid for different values of $\boldsymbol{P}_{t-1}$ with one notable exception: the local instability becomes weaker when $\boldsymbol{P}_{t-1}$ is higher. Indeed, as showed in Table C2, the dominant root $|\lambda_1|$ declines and is not statistically different from 1 across most quantiles $\boldsymbol{q}$ when prices

$\boldsymbol{P}_{t-1}$ are high. These effects of $\boldsymbol{P}_{t-1}$ on $|\lambda_1(\boldsymbol{q}, \boldsymbol{P}_{t-1})|$) reflect the role of nonlinear dynamics. The results reported in Table 6 and in Appendix C indicate that local instability holds for median and lower values of $\boldsymbol{P}_{t-1}$. In these cases, we find strong statistical evidence of local instability but only in the lower tail of the oil price distribution. Again, this stresses the need to explore price dynamics allowing price adjustments to vary with market conditions (as reflected by quantiles).

[PLEASE INSERT TABLE 6 HERE]

The result that dynamic instability is more prevalent under a bearish oil market is consistent with the QVAR estimates in two ways. First, the estimates reported in Table 4 indicate a short-term "overreaction" in the lower tail of the oil price distribution: the coefficient of $p_{o,t-1}$ is greater than 1 in the lower tail (with $q_o \leq 0.3$). Second, as discussed above, nonlinear dynamics contributes to increasing locally instability in the oil market when the oil price is low. Thus, bearish conditions in the oil market combining low oil price and negative shocks contribute to increasing local instability in the oil market.

Finding local instability in the lower tail of the oil price indicates that negative shocks in the oil market contribute to some overreaction in oil price adjustments. Such patterns reveal booms and busts in the oil industry. For example, 2015 was a period of low oil prices due to a strong dollar, ample supply, growing oil stockpiles and a weakening in the world economy. This reflects that oil is one of the most important commodities in the world: it is an input and a source of energy used in the production and marketing of many goods and services. Finding evidence of overreaction in oil price dynamics indicates the presence of complex relationships between oil production, oil prices and real economic activity (Hamilton, 1996, 2003; Elder & Serletis, 2010; Moshiri & Banihashem, 2012).

Note that adverse shocks leading to lower oil prices benefit the industries using oil as an input, indicating that such industries would have weak incentives to prevent price busts. Such behavior could help explain why oil price instability is found in the lower tail of the oil price distribution.[18] And through price linkages across markets, this instability translates into local instability across all three markets (as reflected by a dominant root that is outside the unit circle). These findings highlight the importance of accounting for nonlinearity and tail-specific dependence structure in food and fuel analysis.

6.2. Dynamic Response Analysis

As discussed in section 3, the QVAR model allows us to assess the dynamic responses to exogenous price shocks in the corn, ethanol, and crude oil markets. In each commodity market, under given initial conditions $\boldsymbol{P}_{0s}$, we obtained random draws from the price distribution estimated from our QVAR model in equation (5) along with an estimate of the copula in (8); then, we proceeded forward one week at a time for a total of 400 weeks (where $TT = 400$). Next, we repeated the simulation exercise $D = 500$ times, giving 500 simulated prices generating the forward price distributions and their moments $M_{jit}^{e}(\boldsymbol{P}_{0s})$ given in equations (9a)-(9b). We repeated the process under alternative initial conditions $\boldsymbol{P}_{0s'}$, generating estimates of $M_{jit}^{e}(\boldsymbol{P}_{0s'})$, with $[M_{jit}^{e}(\boldsymbol{P}_{0s'}) - M_{jit}^{e}(\boldsymbol{P}_{0s})]$ providing estimates of the dynamic effects of a change in $\boldsymbol{P}_{0s}$. When the change from $\boldsymbol{P}_{0s}$ to $\boldsymbol{P}_{0s'}$ corresponds to a change in a specific initial price, we interpret $[M_{jit}^{e}(\boldsymbol{P}_{0s'}) - M_{jit}^{e}(\boldsymbol{P}_{0s})]$ as an estimated impulse response function. To test hypotheses about dynamic responses, we bootstrapped the above scheme 1000 times to estimate the distribution of $[M_{jit}^{e}(\boldsymbol{P}_{0s'}) - M_{jit}^{e}(\boldsymbol{P}_{0s})]$. We used this bootstrapped distribution to evaluate the precision in the estimated impulse response functions.[19] Figures 2-4 report the estimated dynamic responses to a 10% increase in each initial price, measured in terms of its effects on four moments: mean, standard deviation, skewness, and kurtosis.[20] We interpret these as estimates of impulse response functions. The effects on skewness correspond to changing asymmetry in the probability function, while the effects on kurtosis reflect changing "fat tailed" properties of the probability function. Figures 2-4 also present the 90% confidence intervals from the bootstrapped distribution of $[M_{jit}^{e}(\boldsymbol{P}_{0s'}) - M_{jit}^{e}(\boldsymbol{P}_{0s})]$.[21]

Figures 2-4 show the nature of dynamic responses to price changes across markets.[22] We find that all price responses eventually die down, reflecting the global stability of stochastic price dynamics. This is an important result: while we uncovered evidence of local instability (e.g., in the lower tail of the oil price distribution), findings of no long-term effects of changes in initial conditions indicate that local stability effects dominate. In other words, the joint distribution of prices for corn, ethanol, and oil is globally stable.

[PLEASE INSERT FIGURE 2 HERE]

Figure 2 reports strong and positive mean responses of corn and crude oil prices to a change in each own price. Note that these responses are slow and last over 250 weeks. In contrast, the mean response of ethanol to own-price change is short-lived: it only lasts for about 30 weeks. In terms of cross-market effects, a 10% increase in oil price has positive impacts on mean corn and ethanol price, effects that last for around 200 weeks. Similar but slightly stronger results are obtained for the dynamic cross effects of corn price on mean oil price. In contrast, a 10% rise in ethanol price is found to have smaller effects on the mean prices of corn and oil, the effects being positive on oil price (reflecting that ethanol and oil are substitutes sources of energy) but negative on corn price.

The dynamic responses on higher moments illustrate how our approach provides new and useful information on food-fuel price dynamics. The effects of changes in initial prices on higher moments of their distribution are more complex (Keweloh, 2021). The impacts on standard deviations reflect evolving price volatility across markets. The own effects of a 10% rise in corn price on its standard deviation are strong and positive, lasting nearly 300 weeks. In contrast, a 10% rise in oil price would reduce the oil price volatility. The cross-market effects reported in Figure 2 show the presence of much heterogeneity. For example, a 10% rise in oil price leads to an increase in price volatility for ethanol. But a similar change would reduce corn price volatility in the short term while increasing it in the longer term (beyond 10 weeks). This result is consistent with the findings of Ahmadi et al. (2016) who documented that an increase in the price of oil due to a positive global demand shock decreases the volatility of the corn price for both the pre- and post-break periods. Importantly, contrary to an argument commonly made by market analysts (Nazlioglu et al., 2013), such findings indicate that higher oil prices do <u>not</u> generally lead to higher commodity prices and higher volatility. Such results reflect the complex dynamic interactions between supply and demand in agricultural markets (Antonakakis & Filis, 2013; Newton & Kuethe, 2015; Ahmadi et al., 2016).

[PLEASE INSERT FIGURE 3 HERE]

Figure 3 shows the effects of initial price changes on price skewness. A 10% rise in oil price would increase the skewness of corn price; but it significantly decreases the skewness of oil price. Importantly, these effects only occur in the short term. The effects of a 10% increase in corn price are more complex: 1) a higher corn price increases the price skewness for ethanol and oil; 2) it reduces the skewness of corn price in the short term; but 3) it tends to significantly increase the skewness of corn prices in the intermediate term (around 80 weeks). In addition, we find that the shocks from corn markets have long-term impacts on ethanol and oil price skewness after more than 150 weeks. This result is new. It contrasts with the findings from Jondeau & Rockinger (2009), who noted that the effects on skewness and kurtosis are short-lived, and the initial response is offset after a few days. Such results illustrate the complex dynamic interactions taking place across markets in the longer term and remind market participants to adjust their portfolios after economic crises.

[PLEASE INSERT FIGURE 4 HERE]

The dynamic effects of initial price changes on the evolution of kurtosis are of special interest. Recall that a high kurtosis means a higher likelihood of facing prices in the tails of the price distribution. Some of the kurtosis effects reported in Figure 4 are statistically significant, stressing that exposure to tail risk changes with market conditions. For example, a 10% rise in the price of oil has positive effects on the kurtosis of prices for corn, ethanol and oil in the short term. These results indicate that higher energy prices contribute to increasing the odds of facing rare events (located in the tails of the price distributions). These patterns document the role of fat-tailed distributions and their dynamics in the food-fuel markets. They also illustrate the flexibility of our approach in modeling the evolution of price distributions across markets.

These results stress the need to go beyond mean-variance analysis in the evaluation of price dynamics. They indicate that responses to price shocks can affect higher moments, including skewness and kurtosis. In turn, this is important in risk management as most market participants being averse to both risk and losses would want to know the odds of facing risk in the tails of the price distributions. Our analysis also reveals that dynamic price responses can vary over time, indicating a need to distinguish between short-term effects versus longer-term effects.

7. Conclusion

This paper proposes the dynamic evaluation of a joint distribution based on a two-step econometric approach: a Quantile Vector Autoregression (QVAR) model followed by a Copula model. Applied to multiple markets, the approach generates a consistent estimate of the joint distribution of prices that can be used to assess dynamic price responses. The analysis allows for arbitrary price distributions and their evolution over time, capturing own and cross-market dynamic effects as well as contemporaneous codependence across markets. The approach provides a flexible representation of the dynamics of all moments of prices. Its usefulness is illustrated in an application to fuel and food markets based on weekly data over the period 2010-2020.

The empirical analysis generates several key findings. First, the QVAR-Copula approach provides statistical evidence of deep linkages among corn, ethanol, and crude oil markets. The QVAR model provides evidence of dynamics in the price distributions, capturing own-price and cross-price effects that vary across quantiles. The estimation of a copula documents that, while positive, the contemporaneous codependence varies with market conditions (i.e., across quantiles). Second, the analysis illustrates how market dynamics affect all moments of the price distributions, stressing the importance of going beyond a mean-variance analysis. Third, we find evidence of nonlinear dynamics which arise mostly in the tails of the price distributions. Fourth, our results show the presence of local instability in the food and fuel system, with instability occurring in the lower tail of the oil price distribution. These results stress the usefulness of our QVAR approach and the importance of allowing dynamic effects to vary across quantiles. Fifth, relying on our estimated model, we use stochastic simulation to evaluate the dynamic responses of the joint price distribution to exogenous shocks. The analysis provides a multi-market evaluation of the evolution of mean, standard deviation, skewness and kurtosis of each price in response to changes in market conditions. We find that price shocks from oil markets not only affect mean and variance of agricultural and biofuel markets, but often contribute to higher moments of their distributions. The analysis is far beyond the estimates with a VAR or GARCH model. The results also highlight the importance of examining the dynamics of tail risk and the need to distinguish between short-term versus longer-term responses.

Our empirical findings have implications for both market participants and policymakers. For example, we find evidence of a changing relationship among oil, ethanol, and corn prices across quantiles. This reflects how changing market conditions (bearish, normal, or bullish) affect tail risk. Also, the strengthening of the food-fuel nexus due to biofuel policy emerges as a cornerstone in the interplay of the world's most critical markets. Our analysis shows that both linear and nonlinear interconnections exist between energy and agricultural markets, which arise in part in the tails of the price distributions. Such patterns stress the need to understand better extreme market behavior, especially the nature of tail risk and its evolution across markets. In this context, our analysis provides useful insights into the impacts of shocks on higher moments of price distribution. Such shocks in supply/demand conditions can come from multiple sources: fluctuations in OPEC’s oil production; the Ukraine war; growth in the renewable energy sectors (e.g., solar power); evolving technology (e.g., electric cars reducing the demand for gasoline); climate change, etc. The shocks can also come from policy change (e.g., evolving biofuel policy). Such changes clearly influence price volatility in agricultural and energy markets, thus affecting risk exposure for market participants. For example, we find local instability of oil price in the lower tail, and a longer-term impact from corn shocks on the price skewness for ethanol and oil. Knowing these patterns can help policymakers and investors design strategies to improve risk management in the short-term, medium-term, and longer-term.

Our proposed approach could be extended in several directions. First, there is a need to refine the analysis of nonlinear dynamics and their implications for market dynamics. Second, while we uncovered evidence of local dynamic instability, it would be useful to examine the linkages between local instability and global instability. Third, while our two-step approach generates consistent estimates of the joint distribution, other estimation methods could possibly benefit from efficiency gains. Fourth, while most previous empirical studies focused on the relation between oil, ethanol, and corn prices, the nature of time-varying causal linkages needs further investigation. Finally, while our application focused on the food/fuel markets, it would be useful to apply our approach to other markets or economic situations. These issues appear to be good topics for future research.

References

Abdelradi, F., & Serra, T. (2015). Asymmetric price volatility transmission between food and energy markets: The case of Spain. *Agricultural Economics*, 46(4), 503-513. https://doi.org/10.1111/agec.12177

Ahmadi, M., Behmiri, N. B., & Manera, M. (2016). How is volatility in commodity markets linked to oil price shocks?. *Energy Economics*, 59, 11-23. https://doi.org/10.1016/j.eneco.2016.07.006

Albulescu, C. T., Tiwari, A. K., & Ji, Q. (2020). Copula-based local dependence among energy, agriculture and metal commodities markets. *Energy*, 202, 117762. https://doi.org/10.1016/j.energy.2020.117762

Antonakakis, N., & Filis, G. (2013). Oil prices and stock market correlation: a time-varying approach. *International Journal of Energy and Statistics*, 1(01), 17-29. https://doi.org/10.1142/S2335680413500026

Balcombe, K., & Rapsomanikis, G. (2008). Bayesian estimation and selection of nonlinear vector error correction models: The case of the sugar-ethanol-oil nexus in Brazil. *American Journal of Agricultural Economics*, 90(3), 658-668. https://doi.org/10.1111/j.1467-8276.2008.01136.x

Bauwens, L., Laurent, S., & Rombouts, J. V. (2006). Multivariate GARCH models: a survey. *Journal of Applied Econometrics*, 21(1), 79-109. https://doi.org/10.1002/jae.842

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), 307-327. https://doi.org/10.1016/0304-4076(86)90063-1

Bruno, V. G., Büyükşahin, B., & Robe, M. A. (2017). The financialization of food?. *American Journal of Agricultural Economics*, 99(1), 243-264. https://doi.org/10.1093/ajae/aaw059

Carlier, G., Chernozhukov, V., De Bie, G., & Galichon, A. (2022). Vector quantile regression and optimal transport, from theory to numerics. *Empirical Economics*, 62, 35-62. https://doi.org/10.1007/s00181-020-01919-y

Ciaian, P. (2011). Food, energy and environment: Is bioenergy the missing link?. *Food Policy*, 36(5), 571-580. https://doi.org/10.1016/j.foodpol.2011.06.008

Chavas, J. P. (2018). On multivariate quantile regression analysis. *Statistical Methods & Applications*, 27, 365-384. https://doi.org/10.1007/s10260-017-0407-x

Chavas, J. P., & Li, J. (2020). A quantile autoregression analysis of price volatility in agricultural markets. *Agricultural Economics*, 51(2), 273-289. https://doi.org/10.1111/agec.12554

Cheng, S., & Cao, Y. (2019). On the relation between global food and crude oil prices: An empirical investigation in a nonlinear framework. *Energy Economics*, 81, 422-432. https://doi.org/10.1016/j.eneco.2019.04.007

Cheng, D., Liao, Y., & Pan, Z. (2023). The geopolitical risk premium in the commodity futures market. *Journal of Futures Markets*, 43(8), 1069-1090. https://doi.org/10.1002/fut.22398

Chernozhukov, V., Fernández-Val, I., & Melly, B. (2013). Inference on counterfactual distributions. *Econometrica*, 81(6), 2205-2268. https://doi.org/10.3982/ECTA10582

Chernozhukov, V., Galichon, A., Hallin, M., & Henry, M. (2017). Monge–Kantorovich depth, quantiles, ranks and signs. *Annals of Statistics*, 45, 223-256. https://doi.org/10.1214/16-AOS1450

Chiou-Wei, S. Z., Chen, S. H., & Zhu, Z. (2019). Energy and agricultural commodity markets interaction: an analysis of crude oil, natural gas, corn, soybean, and ethanol prices. *The Energy Journal*, 40(2), 265-296. https://doi.org/10.5547/01956574.40.2.schi

Du, X., & McPhail, L. L. (2012). Inside the black box: the price linkage and transmission between energy and agricultural markets. *The Energy Journal*, 33(2), 171-194. https://doi.org/10.5547/01956574.33.2.8

Efron, B., & Tibshirani, R. J. (1994). *An Introduction to the Bootstrap*. Chapman and Hall/CRC. https://doi.org/10.1201/9780429246593

Elder, J., & Serletis, A. (2010). Oil price uncertainty. *Journal of Money, Credit and Banking*, 42(6), 1137-1159. https://doi.org/10.1111/j.1538-4616.2010.00323.x

Enders, W. (2010). *Applied Econometric Time-Series*. Third Edition, John Wiley and Sons, New York.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50(4), 987-1007. https://www.jstor.org/stable/1912773

Farid, S., Naeem, M. A., Paltrinieri, A., & Nepal, R. (2022). Impact of COVID-19 on the quantile connectedness between energy, metals and agriculture commodities. *Energy Economics*, 109, 105962. https://doi.org/10.1016/j.eneco.2022.105962

Ghorbel, A., Hamma, W., & Jarboui, A. (2017). Dependence between oil and commodities markets using time-varying Archimedean copulas and effectiveness of hedging strategies. *Journal of Applied Statistics*, 44(9), 1509-1542. https://doi.org/10.1080/02664763.2016.1155107

Ghosal, P., & Sen, B. (2022). Multivariate ranks and quantiles using optimal transport: Consistency, rates and nonparametric testing. *The Annals of Statistics*, 50(2), 1012-1037. https://doi.org/10.1214/21-AOS2136

Hallin, M., Paindaveine, D., Šiman, M., Wei, Y., Serfling, R., Zuo, Y., Kong, L., & Mizera, I. (2010). Multivariate quantiles and multiple-output regression quantiles: from L_1 optimization to half-space depth. *The Annals of Statistics*, 38(2), 635–703. http://www.jstor.org/stable/25662257

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, 57(2), 357–384. https://doi.org/10.2307/1912559

Hamilton, J.D. (1994) *Time Series Analysis*. Princeton University Press, Princeton.

Hamilton, J. D. (1996). This is what happened to the oil price-macroeconomy relationship. *Journal of Monetary Economics*, 38(2), 215-220. https://doi.org/10.1016/S0304-3932(96)01282-2

Hamilton, J. D. (2003). What is an oil shock?. *Journal of Econometrics*, 113(2), 363-398. https://doi.org/10.1016/S0304-4076(02)00207-5

Hanif, W., Hernandez, J. A., Shahzad, S. J. H., & Yoon, S. M. (2021). Tail dependence risk and spillovers between oil and food prices. *The Quarterly Review of Economics and Finance*, 80, 195-209. https://doi.org/10.1016/j.qref.2021.01.019

Harvey, C. R., Liechty, J. C., Liechty, M. W., & Müller, P. (2010). Portfolio selection with higher moments. *Quantitative Finance*, 10(5), 469-485. https://doi.org/10.1080/14697681003756877

Hasselblatt, B., & Katok, A. (2003). *A First Course in Dynamics*. Cambridge University Press, New York.

Hayashi, F. (2000). *Econometrics*. Princeton University Press, Princeton.

Herwartz, H., & Saucedo, A. (2020). Food–oil volatility spillovers and the impact of distinct biofuel policies on price uncertainties on feedstock markets. *Agricultural Economics*, 51(3), 387-402. https://doi.org/10.1111/agec.12561

Hochman, G., Rajagopal, D., & Zilberman, D. (2010). Are biofuels the culprit? OPEC, food, and fuel. *American Economic Review*, 100(2), 183-187. https://doi.org/10.1257/aer.100.2.183

Hochman, G., & Zilberman, D. (2018). Corn ethanol and U.S. biofuel policy 10 years later: A quantitative assessment. *American Journal of Agricultural Economics*, 100, 570–584. https://doi.org/10.1093/ajae/aax105

Janda, K., & Krištoufek, L. (2019). The relationship between fuel and food prices: Methods and outcomes. *Annual Review of Resource Economics*, 11, 195-216. https://doi.org/10.1146/annurev-resource-100518-094012

Ji, Q., Bouri, E., Roubaud, D., & Shahzad, S. J. H. (2018). Risk spillover between energy and agricultural commodity markets: A dependence-switching CoVaR-copula model. *Energy Economics*, 75, 14-27. https://doi.org/10.1016/j.eneco.2018.08.015

Joe, H. (2015). *Dependence Modeling with Copulas.* CRC Press, New York.

Jondeau, E., & Rockinger, M. (2006). Optimal portfolio allocation under higher moments. *European Financial Management*, 12(1), 29-55. https://doi.org/10.1111/j.1354-7798.2006.00309.x

Jondeau, E., & Rockinger, M. (2009). The impact of shocks on higher moments. *Journal of Financial Econometrics*, 7(2), 77-105. https://doi.org/10.1093/jjfinec/nbn017

Keweloh, S. A. (2021). A generalized method of moments estimator for structural vector autoregressions based on higher moments. *Journal of Business & Economic Statistics*, 39(3), 772-782. https://doi.org/10.1080/07350015.2020.1730858

Khalfaoui, R., Baumöhl, E., Sarwar, S., & Výrost, T. (2021). Connectedness between energy and nonenergy commodity markets: Evidence from quantile coherency networks. *Resources Policy*, 74, 102318. https://doi.org/10.1016/j.resourpol.2021.102318

Koenker, R. (2005). *Quantile Regression.* Cambridge University Press, Cambridge.

Koenker, R., & Machado, J. A. (1999). Goodness of fit and related inference processes for quantile regression. *Journal of the American Statistical Association*, 94(448), 1296-1310. https://doi.org/10.1080/01621459.1999.10473882

Koenker, R., & Xiao, Z. (2004). Unit root quantile autoregression inference. *Journal of the American Statistical Association*, 99(467), 775-787. https://doi.org/10.1198/016214504000001114

Koenker, R., & Xiao, Z. (2006). Quantile autoregression. *Journal of the American Statistical Association*, 101(475), 980-990. https://doi.org/10.1198/016214506000000672

Kong, L., & Mizera, I. (2012). Quantile tomography: using quantiles with multivariate data. *Statistica Sinica*, 1589-1610. https://www.jstor.org/stable/24310188

Kumar, S., Tiwari, A. K., Raheem, I. D., & Hille, E. (2021). Time-varying dependence structure between oil and agricultural commodity markets: A dependence-switching CoVaR copula approach. *Resources Policy*, 72, 102049. https://doi.org/10.1016/j.resourpol.2021.102049

Lee, D. J., Kim, T. H., & Mizen, P. (2021). Impulse response analysis in conditional quantile models with an application to monetary policy. *Journal of Economic Dynamics and Control*, 127, 104102. https://doi.org/10.1016/j.jedc.2021.104102

Li, J., Chavas, J. P., & Li, C. (2022). The dynamic effects of price support policy on price volatility: The case of the rice market in China. *Agricultural Economics*, 53(2), 307-320. https://doi.org/10.1111/agec.12681

Li, J., & Chavas, J. P. (2023). A dynamic analysis of the distribution of commodity futures and spot prices. *American Journal of Agricultural Economics*, 105(1), 122-143. https://doi.org/10.1111/ajae.12309

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, 7(1), 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

Mensi, W., Tiwari, A., Bouri, E., Roubaud, D., & Al-Yahyaee, K. H. (2017). The dependence structure across oil, wheat, and corn: A wavelet-based copula approach using implied volatility indexes. *Energy Economics*, 66, 122-139. https://doi.org/10.1016/j.eneco.2017.06.007

Mokni, K., & Ben-Salha, O. (2020). Asymmetric causality in quantiles analysis of the oil-food nexus since the 1960s. *Resources Policy*, 69, 101874. https://doi.org/10.1016/j.resourpol.2020.101874

Moshiri, S., & Banihashem, A. (2012). Asymmetric effects of oil price shocks on economic growth of oil-exporting countries. USAEE Working Paper. http://dx.doi.org/10.2139/ssrn.2006763

Murphy, K. M., & Topel, R. H. (2002). Estimation and inference in two-step econometric models. *Journal of Business & Economic Statistics*, 20(1), 88-97. https://doi.org/10.1198/073500102753410417

Nazlioglu, S., Erdem, C., & Soytas, U. (2013). Volatility spillover between oil and agricultural commodity markets. *Energy Economics*, 36, 658-665. https://doi.org/10.1016/j.eneco.2012.11.009

Nelsen, R. B. (2006). *An Introduction to Copula.* Springer, New York.

Newton, J., & T. Kuethe. (2015). Changing landscape of corn and soybean production and potential implications in 2015. *Farmdoc Daily*, 5(42).

Pal, D., & Mitra, S. K. (2017). Time-frequency contained co-movement of crude oil and world food prices: A wavelet-based analysis. *Energy Economics*, 62, 230-239. https://doi.org/10.1016/j.eneco.2016.12.020

Plagborg-Møller, M., & Wolf, C. K. (2021). Local projections and VARs estimate the same impulse responses. *Econometrica*, 89(2), 955-980. https://doi.org/10.3982/ECTA17813

Rafiq, S., & Bloch, H. (2016). Explaining commodity prices through asymmetric oil shocks: Evidence from nonlinear models. *Resources Policy*, 50, 34-48. https://doi.org/10.1016/j.resourpol.2016.08.005

Reboredo, J. C. (2012). Do food and oil prices co-move?. *Energy Policy*, 49, 456-467. https://doi.org/10.1016/j.enpol.2012.06.035

Saghaian, S., Nemati, M., Walters, C., & Chen, B. (2018). Asymmetric price volatility transmission between US biofuel, corn, and oil markets. *Journal of Agricultural and Resource Economics*, 46-60. https://doi.org/10.22004/ag.econ.267609

Schwarz, G. (1978). Estimating the dimension of a model. The Annals of Statistics, 461-464. https://www.jstor.org/stable/2958889

Serra, T., Zilberman, D., Gil, J. M., & Goodwin, B. K. (2011). Nonlinearities in the US corn-ethanol-oil-gasoline price system. *Agricultural Economics*, 42(1), 35-45. https://doi.org/10.1111/j.1574-0862.2010.00464.x

Serra, T., & Zilberman, D. (2013). Biofuel-related price transmission literature: A review. *Energy Economics*, 37, 141-151. https://doi.org/10.1016/j.eneco.2013.02.014

Sklar, A. (1959). Fonctions de Répartition à n Dimensions et Leurs Marges. *Institut Statistique de l'Université de Paris*, 8, 229-231.

Sun, Y., Gao, P., Raza, S. A., Shah, N., & Sharif, A. (2023). The asymmetric effects of oil price shocks on the world food prices: Fresh evidence from quantile-on-quantile regression approach. *Energy*, 270, 126812. https://doi.org/10.1016/j.energy.2023.126812

Tang, K., & Xiong, W. (2012). Index investment and the financialization of commodities. Financial Analysts Journal, 68(6), 54-74. https://doi.org/10.2469/faj.v68.n6.5

Tiwari, A. K., Abakah, E. J. A., Adewuyi, A. O., & Lee, C. C. (2022). Quantile risk spillovers between energy and agricultural commodity markets: Evidence from pre and during COVID-19 outbreak. *Energy Economics*, 113, 106235. https://doi.org/10.1016/j.eneco.2022.106235

Tyner, W. E. (2010). The integration of energy and agricultural markets. *Agricultural Economics*, 41, 193-201. https://doi.org/10.1111/j.1574-0862.2010.00500.x

Van der Vaart, A. W. (1998). *Asymptotic Statistics*. Cambridge University Press, New York.

Vo, D. H., Vu, T. N., Vo, A. T., & McAleer, M. (2019). Modeling the relationship between crude oil and agricultural commodity prices. *Energies*, 12(7), 1344. https://doi.org/10.3390/en12071344

Vu, T. N., Vo, D. H., Ho, C. M., & Van, L. T. H. (2019). Modeling the impact of agricultural shocks on oil price in the US: a new approach. *Journal of Risk and Financial Management*, 12(3), 147. https://doi.org/10.3390/jrfm12030147

Wang, L., Chavas, J. P., & Li, J. (2023). The dynamic impacts of disease outbreak on vertical and spatial markets: the case of African Swine Fever in China. *Applied Economics*, 55(18), 2005-2023. https://doi.org/10.1080/00036846.2022.2101605

Wei, Y. (2008). An approach to multivariate covariate-dependent quantile contours with application to bivariate conditional growth charts. *Journal of the American Statistical Association*, 103(481), 397-409. https://doi.org/10.1198/016214507000001472

White, H., Kim, T. H., & Manganelli, S. (2015). VAR for VaR: Measuring tail dependence using multivariate regression quantiles. *Journal of Econometrics*, 187(1), 169-188. https://doi.org/10.1016/j.jeconom.2015.02.004

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. Second Edition, MIT Press, Cambridge.

Wright, B. (2014). Global biofuels: key to the puzzle of grain market behavior. *Journal of Economic Perspectives*, 28(1), 73-98. https://doi.org/10.1257/jep.28.1.73

Wu, Z., Weersink, A., & Maynard, A. (2022). Fuel-feed-livestock price linkages under structural changes. *Applied Economics*, 54(2), 206-223. https://doi.org/10.1080/00036846.2021.1965082

Zilberman, D., Hochman, G., Rajagopal, D., Sexton, S., & Timilsina, G. (2013). The impact of biofuels on commodity food prices: Assessment of findings. *American Journal of Agricultural Economics*, 95(2), 275-281. https://doi.org/10.1093/ajae/aas037

Zhang, H., Jin, C., Bouri, E., Gao, W., & Xu, Y. (2023). Realized higher-order moments spillovers between commodity and stock markets: Evidence from China. *Journal of Commodity Markets*, 30, 100275. https://doi.org/10.1016/j.jcomm.2022.100275

Zhang, Z., Lohr, L., Escalante, C., & Wetzstein, M. (2009). Ethanol, corn, and soybean price relations in a volatile vehicle-fuels market. *Energies*, 2(2), 320-339. https://doi.org/10.3390/en20200320

Table 1. Summary statistics for food and fuel markets, 2010-2021

Log Prices Index ($\log(100 * P_{i,t}/P_{i,1})$)			
	Corn (P_c)	Ethanol (P_e)	Crude Oil (P_o)
Mean	4.648	4.484	4.371
Median	4.514	4.404	4.369
Std. Dev.	0.263	0.245	0.362
Skewness	0.936	0.321	-0.594
Excess Kurtosis	-0.604	-0.811	0.236
Minimum	4.311	3.773	2.807
Date (min.)	April 8, 2020	March 4, 2020	March 25, 2020
Maximum	5.288	5.005	4.909
Date (max.)	July 25, 2012	June 29, 2011	March 30, 2011
Jarque-Bera	89.265[a]	24.423[a]	34.158[a]

Note: [a] indicate rejection of the null hypothesis at the 1% significant level.

Table 2. QVAR estimates with selected quantiles: corn equation

Variable	Quantile Estimates								
	$q_c = 0.1$	$q_c = 0.2$	$q_c = 0.3$	$q_c = 0.4$	$q_c = 0.5$	$q_c = 0.6$	$q_c = 0.7$	$q_c = 0.8$	$q_c = 0.9$
$P_{c,t-1}$	0.917***	0.917***	0.927***	0.990***	1.000***	1.003***	0.903***	0.827***	0.709***
	(0.038)	(0.030)	(0.031)	(0.013)	(0.016)	(0.015)	(0.046)	(0.065)	(0.103)
$P_{e,t-1}$	-0.022	-0.009	-0.003	-0.021	-0.030	-0.027	0.003	-0.003	0.035
	(0.020)	(0.017)	(0.019)	(0.021)	(0.018)	(0.023)	(0.023)	(0.024)	(0.040)
$P_{o,t-1}$	0.023**	0.016*	0.006	0.005	0.002	-0.001	-0.002	-0.006	-0.003
	(0.010)	(0.009)	(0.009)	(0.006)	(0.006)	(0.008)	(0.007)	(0.009)	(0.011)
$P^s_{c,t-1}$	0.096	0.111***	0.086**						
	(0.059)	(0.038)	(0.040)						
$P_{c,t-2}$							0.085*	0.168***	0.253**
							(0.044)	(0.061)	(0.101)
tt				-0.002	-0.004**	-0.005***	-0.003**	-0.005***	-0.005
				(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)
sin	-0.008**	-0.006**	-0.002				0.002	0.002	0.004
	(0.003)	(0.003)	(0.002)				(0.002)	(0.003)	(0.004)
cos	0.012***	0.009***	0.010***				-0.001	-0.005	-0.007*
	(0.003)	(0.003)	(0.003)				(0.002)	(0.003)	(0.004)
$intercept$	0.336**	0.322***	0.301***	0.118*	0.138**	0.132**	0.070	0.104*	0.086
	(0.147)	(0.094)	(0.104)	(0.076)	(0.064)	(0.057)	(0.053)	(0.064)	(0.112)
Obs.	553	553	553	553	553	553	553	553	553
Goodness of fit	0.788	0.816	0.834	0.851	0.870	0.888	0.900	0.899	0.885

Note: Standard errors (presented in parentheses) are obtained using bootstrapping. *, **, and *** indicate significant at the 10%, 5%, and 1% significance levels, respectively. For the "goodness of fit", we report the Pseudo-R^2 proposed by Koenker and Machado (1999) for quantile estimates.

Table 3. QVAR estimates with selected quantiles: ethanol equation

Variable	Quantile Estimates								
	$q_e = 0.1$	$q_e = 0.2$	$q_e = 0.3$	$q_e = 0.4$	$q_e = 0.5$	$q_e = 0.6$	$q_e = 0.7$	$q_e = 0.8$	$q_e = 0.9$
$P_{c,t-1}$	0.081***	0.080***	0.067**	0.046**	0.052**	0.014	-0.005	-0.011	0.011
	(0.028)	(0.018)	(0.022)	(0.021)	(0.021)	(0.021)	(0.018)	(0.018)	(0.032)
$P_{e,t-1}$	0.846***	0.852***	0.874***	0.926***	0.906***	0.958***	0.972***	0.970***	0.960***
	(0.037)	(0.025)	(0.037)	(0.027)	(0.027)	(0.031)	(0.030)	(0.023)	(0.041)
$P_{o,t-1}$	0.114**	0.114***	0.122***	0.097**	0.057	0.005	0.014	0.026***	0.012
	(0.051)	(0.030)	(0.033)	(0.042)	(0.036)	(0.010)	(0.010)	(0.009)	(0.018)
$P^s_{o,t-1}$						0.029*	0.041***	0.044***	0.033
						(0.016)	(0.015)	(0.014)	(0.022)
$P_{o,t-2}$	-0.107**	-0.105***	-0.117***	-0.097***	-0.056**				
	(0.051)	(0.028)	(0.031)	(0.036)	(0.031)				
tt	-0.007***	-0.007***	-0.007***	-0.003	-0.005***	-0.002	-0.002	-0.002	-0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
$intercept$	0.266***	0.245***	0.233***	0.123**	0.192***	0.113**	0.105	0.099	0.126
	(0.078)	(0.053)	(0.072)	(0.066)	(0.060)	(0.067)	(0.083)	(0.075)	(0.114)
Obs.	553	553	553	553	553	553	553	553	553
Goodness of fit	0.800	0.823	0.835	0.846	0.859	0.871	0.876	0.866	0.845

Note: Standard errors (presented in parentheses) are obtained using bootstrapping. *, **, and *** indicate significant at the 10%, 5%, and 1% significance levels, respectively. For the "goodness of fit", we report the Pseudo-R^2 proposed by Koenker and Machado (1999) for quantile estimates.

Table 4. QVAR estimates with selected quantiles: crude oil equation

Variable	Quantile Estimates								
	$q_o = 0.1$	$q_o = 0.2$	$q_o = 0.3$	$q_o = 0.4$	$q_o = 0.5$	$q_o = 0.6$	$q_o = 0.7$	$q_o = 0.8$	$q_o = 0.9$
$P_{c,t-1}$	-0.248**	-0.107	-0.007	0.003	0.001	-0.006	0.000	0.015	0.037*
	(0.109)	(0.070)	(0.020)	(0.021)	(0.019)	(0.018)	(0.016)	(0.019)	(0.020)
$P_{e,t-1}$	0.071*	0.025	0.027	0.030	0.037	0.037*	0.017	-0.017	-0.026
	(0.036)	(0.035)	(0.025)	(0.030)	(0.025)	(0.025)	(0.025)	(0.031)	(0.037)
$P_{o,t-1}$	1.243***	1.210***	1.001***	0.980***	0.969***	0.969***	0.946***	0.949***	0.931***
	(0.117)	(0.097)	(0.013)	(0.014)	(0.014)	(0.011)	(0.012)	(0.012)	(0.019)
$P^s_{o,t-1}$	-0.153***	-0.080					0.082*	0.089*	0.118**
	(0.054)	(0.064)					(0.047)	(0.048)	(0.053)
$P_{c,t-2}$	0.200**	0.111							
	(0.101)	(0.069)							
$P_{o,t-2}$	-0.217*	-0.197**							
	(0.121)	(0.094)							
tt							-0.004**	-0.007**	-0.005**
							(0.002)	(0.003)	(0.002)
$intercept$	-0.247***	-0.212***	-0.113**	-0.067	-0.031	0.013	0.182**	0.273***	0.297***
	(0.084)	(0.068)	(0.047)	(0.040)	(0.032)	(0.041)	(0.080)	(0.085)	(0.089)
Obs.	553	553	553	553	553	553	553	553	553
Goodness of fit	0.864	0.866	0.873	0.880	0.885	0.882	0.874	0.860	0.838

Note: Standard errors (presented in parentheses) are obtained using bootstrapping. *, **, and *** indicate significant at the 10%, 5%, and 1% significance levels, respectively. For the "goodness of fit", we report the Pseudo-R^2 proposed by Koenker and Machado (1999) for quantile estimates.

Table 5. Quantile estimates of Copula functions, conditional on crude oil q_o

Panel A: Corn q_c									
Variable	Quantile Estimates								
	$q_c = 0.1$	$q_c = 0.2$	$q_c = 0.3$	$q_c = 0.4$	$q_c = 0.5$	$q_c = 0.6$	$q_c = 0.7$	$q_c = 0.8$	$q_c = 0.9$
q_o	0.081*	0.203***	0.226***	0.226***	0.221**	0.286***	0.217***	0.230***	0.132***
	(0.043)	(0.055)	(0.064)	(0.076)	(0.076)	(0.078)	(0.080)	(0.055)	(0.040)
$intercept$	0.063***	0.111***	0.202***	0.285***	0.382***	0.466***	0.589***	0.677***	0.821***
	(0.020)	(0.021)	(0.038)	(0.048)	(0.033)	(0.042)	(0.049)	(0.035)	(0.030)
Obs.	553	553	553	553	553	553	553	553	553
Goodness of fit	0.010	0.020	0.024	0.015	0.019	0.023	0.021	0.024	0.019
t- test	-40.303***	-15.615***	-5.508***	-7.436***	NA	4.334***	-6.046***	-11.415***	-30.078***

Panel B: Ethanol q_e									
Variable	Quantile Estimates								
	$q_e = 0.1$	$q_e = 0.2$	$q_e = 0.3$	$q_e = 0.4$	$q_e = 0.5$	$q_e = 0.6$	$q_e = 0.7$	$q_e = 0.8$	$q_e = 0.9$
q_o	0.104**	0.238***	0.314***	0.337***	0.345***	0.340***	0.386***	0.278***	0.176***
	(0.042)	(0.068)	(0.067)	(0.050)	(0.056)	(0.081)	(0.049)	(0.068)	(0.057)
$intercept$	0.052***	0.105***	0.162***	0.247***	0.311***	0.422***	0.492***	0.640***	0.792***
	(0.017)	(0.027)	(0.028)	(0.030)	(0.037)	(0.043)	(0.030)	(0.046)	(0.040)
Obs.	553	553	553	553	553	553	553	553	553
Goodness of fit	0.019	0.033	0.048	0.051	0.054	0.045	0.047	0.034	0.013
t-test	-74.531***	-29.414***	-7.574***	0.667	NA	2.225**	3.235***	-11.986***	-51.140***

Note: Standard errors (presented in parentheses) are obtained using bootstrapping. *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively. For the "goodness of fit", we report the Pseudo-R^2 proposed by Koenker and Machado (1999) for quantile estimates. The t test presents the ratio of the difference of parameter β of other eight quantiles to the median (i.e., q=0.5) using bootstrapping.

Table 6. Estimated modulus of the dominant root $|\lambda_1|$, selected quantiles

q_o \ q_e	0.1	0.3	0.5	0.7	0.9
$|\lambda_1[(q_c = 0.1, q_e, q_o), \boldsymbol{P}_{t-1}]|$					
0.1	1.200***	1.197***	1.210***	1.222***	1.221***
0.3	1.045	1.044	1.046	1.049	1.049
0.5	0.987	0.989	0.986	0.991	0.987
0.7	0.968	0.970	0.969	0.984	0.975
0.9	0.928	0.924	0.911	0.963	0.955
$|\lambda_1[(q_c = 0.5, q_e, q_o), \boldsymbol{P}_{t-1}]|$					
q_o \ q_e	0.1	0.3	0.5	0.7	0.9
0.1	1.210***	1.207***	1.218***	1.228***	1.228***
0.3	1.049	1.048	1.050	1.051	1.051
0.5	0.988	0.990	0.987	1.003	0.990
0.7	0.987	0.988	0.984	1.004	0.985
0.9	0.985	0.986	0.984	0.997	0.975
$|\lambda_1[(q_c = 0.9, q_e, q_o), \boldsymbol{P}_{t-1}]|$					
q_o \ q_e	0.1	0.3	0.5	0.7	0.9
0.1	1.204***	1.200***	1.215***	1.228***	1.228***
0.3	1.044	1.043	1.046	1.050	1.050
0.5	0.994	0.995	0.993	0.990	0.993
0.7	0.983	0.982	0.984	0.976	0.988
0.9	0.983	0.983	0.984	0.979	0.987

Note: The reported modulus of the dominant root $|\lambda_1|$ are evaluated at sample medians. Testing the null hypothesis H_0: $|\lambda_1| < 1$ with bootstrapping, statistical significance of (local) instability is denoted by stars: *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively.

Figure 1. Trajectories of corn, ethanol, and WTI crude oil futures prices, log $(P_{i,t}/P_{i,1} * 100)$, 2010-2021

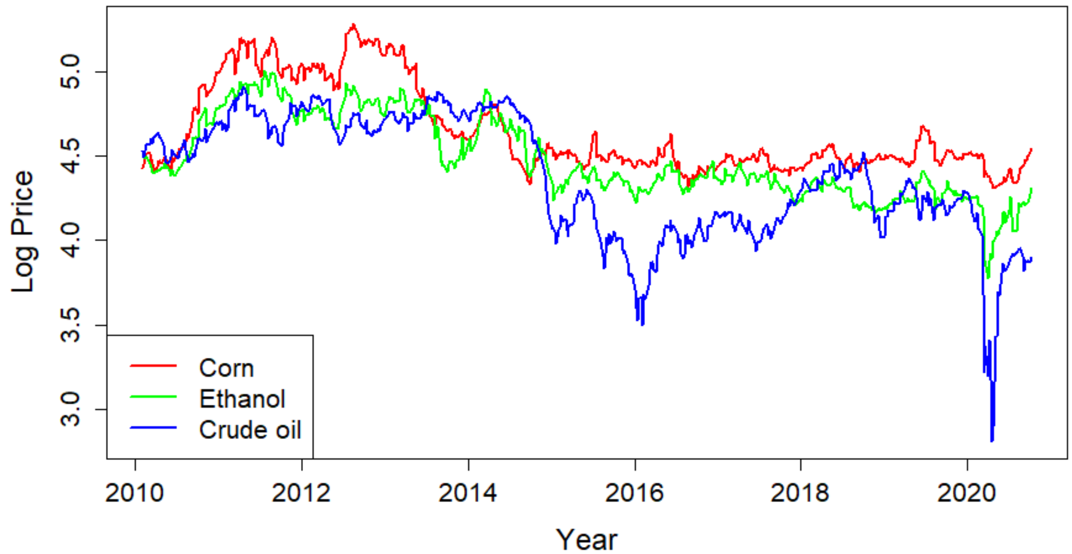
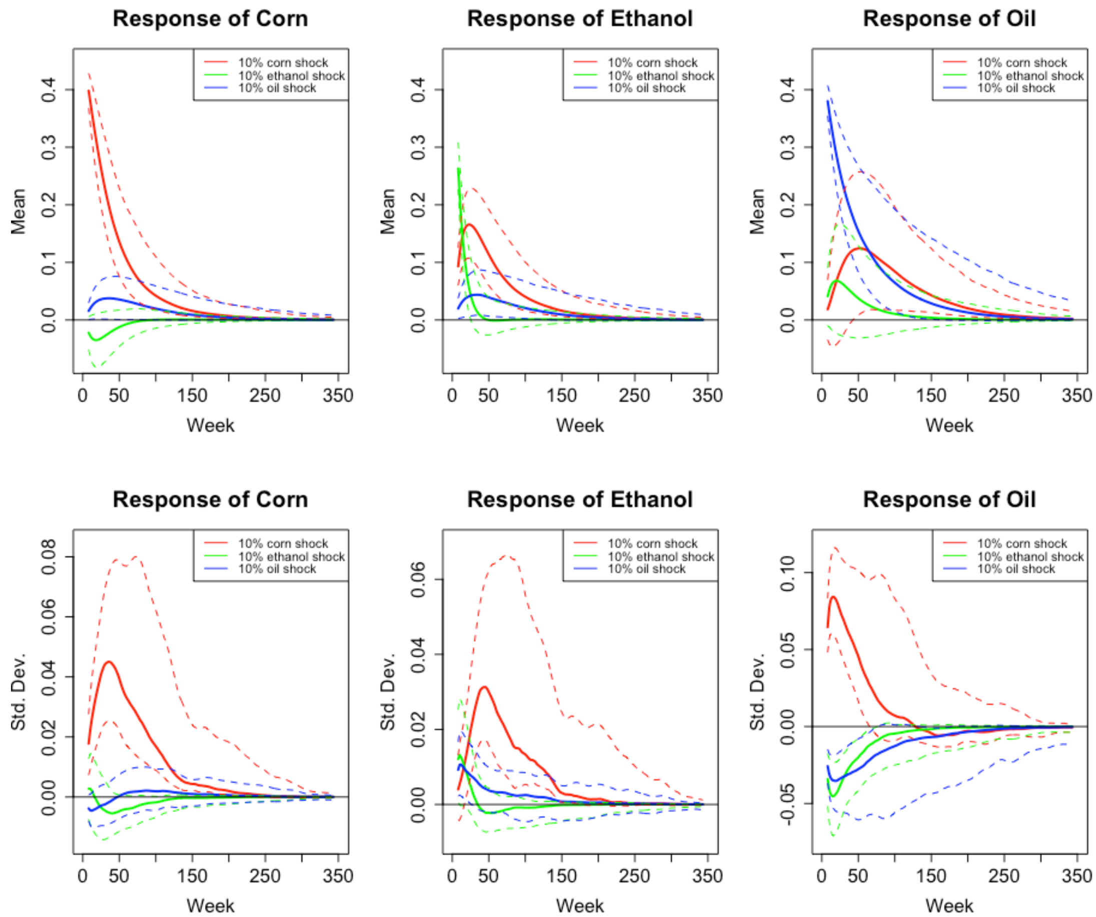
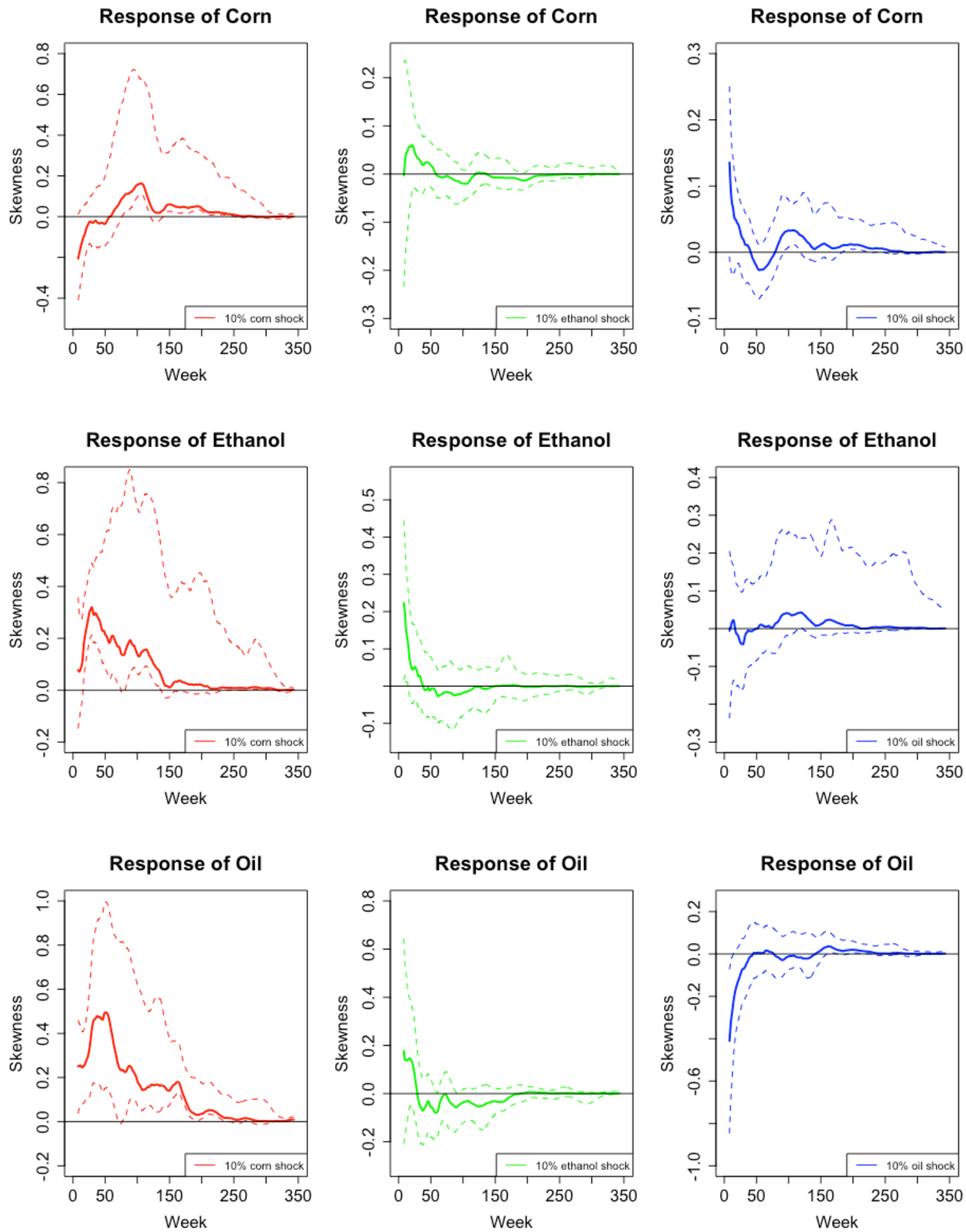


Figure 2. Dynamic responses on price mean and standard deviation



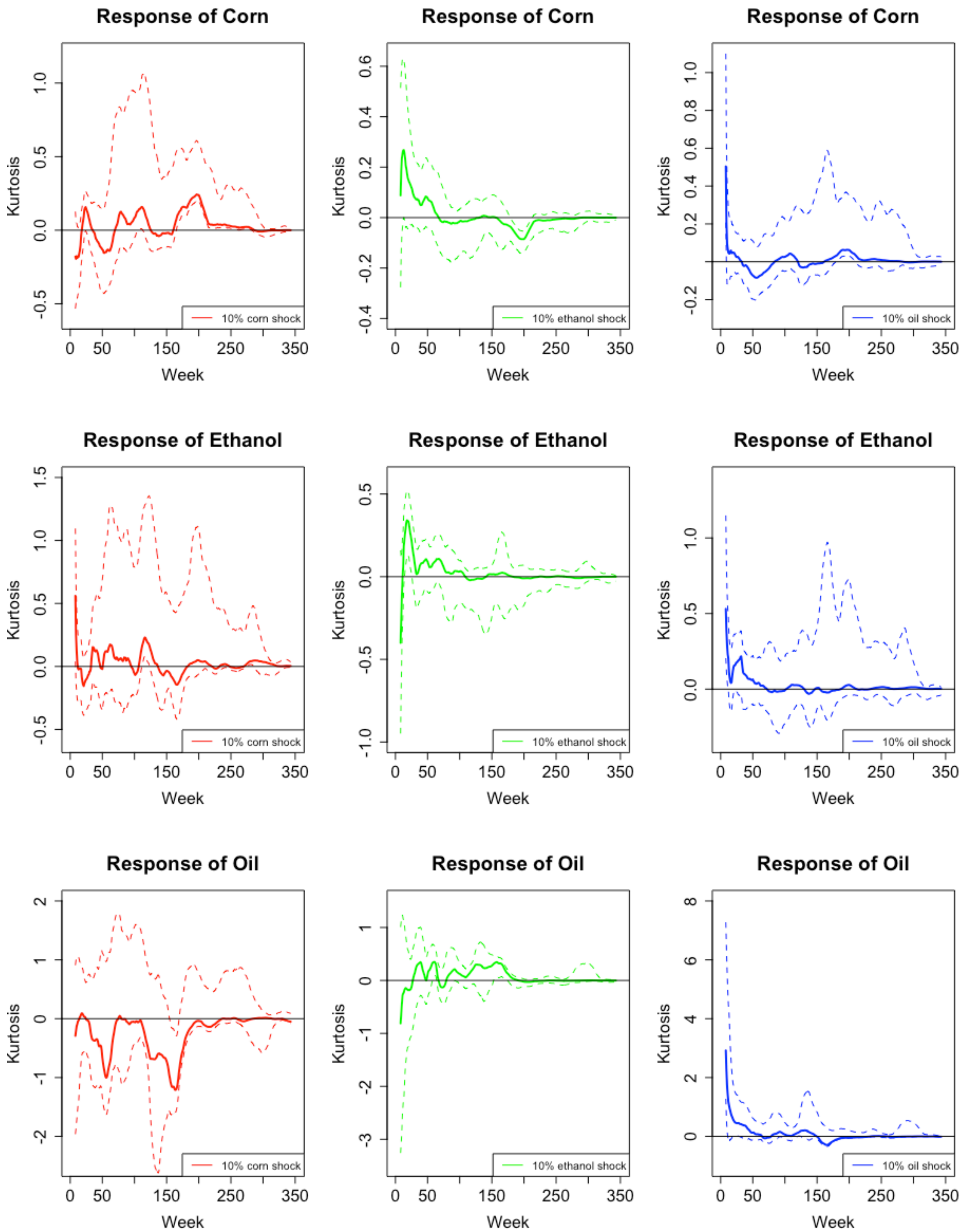
Note: The solid lines show the estimated impulse responses. The dotted lines report the 90% confidence intervals. Take the first graph on the top left for an example, it presents dynamic responses of price mean of corn market following a positive 10% shock to each of three markets, where the red line represents shocks originating from corn market, the green one represents ethanol shocks, and the blue one represents oil shocks.

Figure 3. Dynamic responses on price skewness



Note: The solid lines show the estimated impulse responses. The dotted lines report the 90% confidence intervals. Take the first graph on the top left for an example, the red line presents dynamic responses of price skewness of corn market following a positive 10% shock to own market (i.e., corn market).

Figure 4. Dynamic responses on price kurtosis



Note: The solid lines show the estimated impulse responses. The dotted lines report the 90% confidence intervals. Take the first graph on the top left for an example, the red line presents dynamic responses of price kurtosis of corn market following a positive 10% shock to own market (i.e., corn market).

Appendices

Appendix A: Estimates for a conventional VAR model

Table A1. VAR estimates

Variable	VAR Estimates		
	Corn	Ethanol	Crude oil
$p_{c,t-1}$	0.949*** (0.048)	0.046*** (0.015)	-0.130* (0.073)
$p_{e,t-1}$	-0.025 (0.020)	0.902*** (0.022)	0.051 (0.033)
$p_{o,t-1}$	0.007 (0.008)	0.084*** (0.030)	1.066*** (0.045)
$P^s_{c,t-1}$	0.028 (0.033)		
$P^s_{o,t-1}$		0.008 (0.010)	0.052*** (0.015)
$p_{c,t-2}$	0.026 (0.043)		0.103 (0.072)
$p_{o,t-2}$		-0.076*** (0.028)	-0.085** (0.043)
tt	-0.004** (0.002)	-0.006*** (0.002)	-0.001 (0.003)
sin	-0.002 (0.002)		
cos	0.002 (0.002)		
$intercept$	0.209** (0.091)	0.205*** (0.056)	-0.022 (0.083)
Obs.	553	553	553
Goodness of fit	0.982	0.975	0.975

Note: Standard errors are presented in parentheses; they are obtained using bootstrapping. *, **, and *** indicate significant at the 10%, 5%, and 1% significance levels, respectively. For the "goodness of fit", we report the adjusted R^2 for VAR estimates.

Appendix B: Robustness check on alternative specifications of the Copula functions

Table B1. Quantile estimates of Copula functions, conditional on ethanol q_e

Panel A: Corn q_c

Variable	Quantile Estimates								
	$q_c = 0.1$	$q_c = 0.2$	$q_c = 0.3$	$q_c = 0.4$	$q_c = 0.5$	$q_c = 0.6$	$q_c = 0.7$	$q_c = 0.8$	$q_c = 0.9$
q_e	0.344***	0.516***	0.634***	0.741***	0.767***	0.763***	0.641***	0.571***	0.367***
	(0.051)	(0.046)	(0.044)	(0.053)	(0.047)	(0.048)	(0.051)	(0.042)	(0.049)
$intercept$	0.006	0.022*	0.039***	0.062**	0.123***	0.189***	0.332***	0.426***	0.631***
	(0.008)	(0.013)	(0.013)	(0.025)	(0.027)	(0.035)	(0.039)	(0.034)	(0.044)
Obs.	553	553	553	553	553	553	553	553	553
Goodness of fit	0.123	0.177	0.201	0.206	0.219	0.217	0.210	0.191	0.141
t test	-147.970***	-76.176***	-37.581***	-5.937***	/	-11.951***	-48.110***	-88.116***	-144.690***

Panel B: Crude oil q_o

Variable	Quantile Estimates								
	$q_o = 0.1$	$q_o = 0.2$	$q_o = 0.3$	$q_o = 0.4$	$q_o = 0.5$	$q_o = 0.6$	$q_o = 0.7$	$q_o = 0.8$	$q_o = 0.9$
q_e	0.219***	0.298***	0.366***	0.417***	0.362***	0.325***	0.250***	0.227***	0.120**
	(0.030)	(0.059)	(0.068)	(0.056)	(0.068)	(0.068)	(0.071)	(0.048)	(0.061)
$intercept$	0.013	0.072***	0.135***	0.185***	0.305***	0.417***	0.576***	0.672***	0.825***
	(0.012)	(0.030)	(0.028)	(0.033)	(0.046)	(0.045)	(0.043)	(0.031)	(0.043)
Obs.	553	553	553	553	553	553	553	553	553
Goodness of fit	0.054	0.054	0.057	0.053	0.048	0.032	0.020	0.022	0.005
t test	-48.560***	-22.599***	-6.821***	3.820***	/	-14.952***	-33.451***	-45.720***	-66.890***

Note: Standard errors are presented in parentheses; they are obtained using bootstrapping. *, **, and *** indicate significant at the 10%, 5%, and 1% significance levels, respectively. For the "goodness of fit", we report the Pseudo-R^2 proposed by Koenker and Machado (1999) for quantile estimates. The t test presents the ratio of the difference of parameter β of other eight quantiles to the median (i.e., q=0.5) using bootstrapping.

Table B2. Quantile estimates of Copula functions, conditional on corn q_c

Panel A: Ethanol q_e

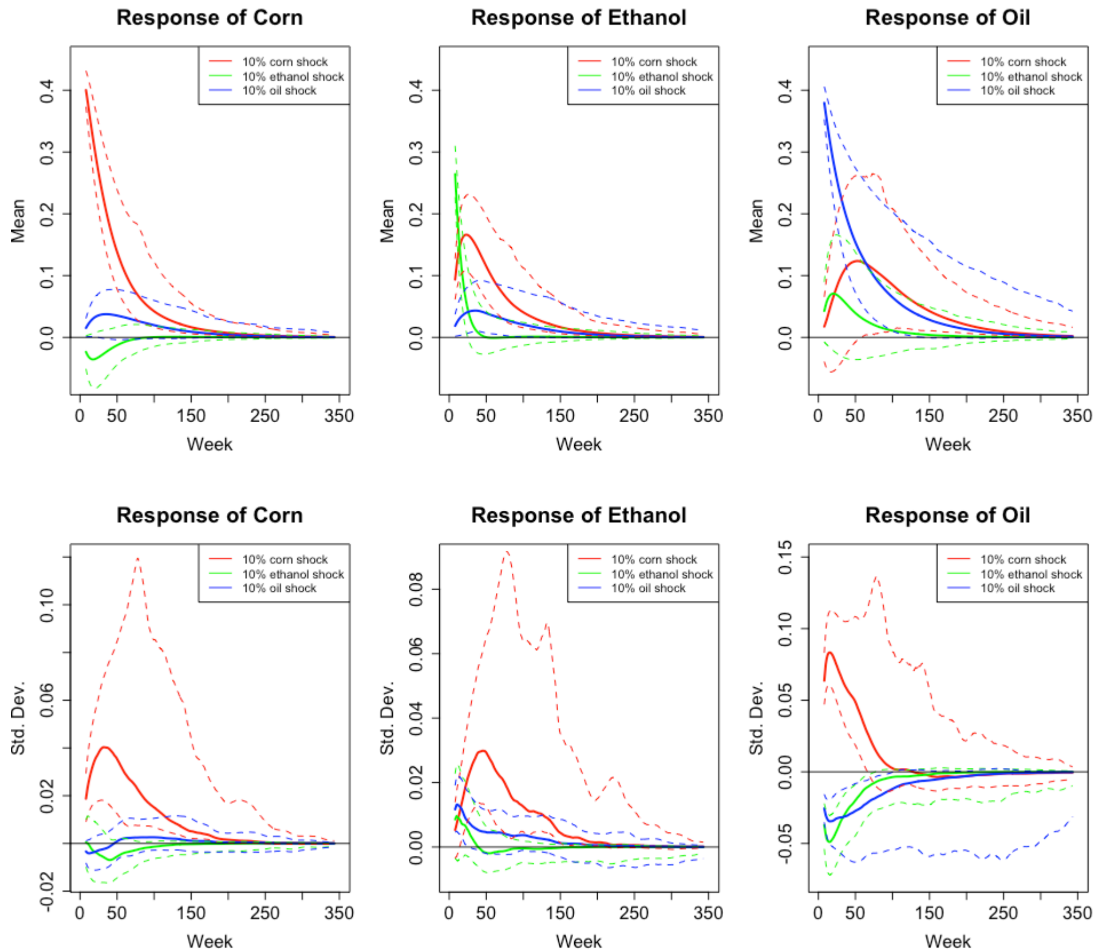
Variable	Quantile Estimates								
	$q_e = 0.1$	$q_e = 0.2$	$q_e = 0.3$	$q_e = 0.4$	$q_e = 0.5$	$q_e = 0.6$	$q_e = 0.7$	$q_e = 0.8$	$q_e = 0.9$
q_c	0.324***	0.539***	0.705***	0.750***	0.739***	0.702***	0.696***	0.515***	0.333***
	(0.045)	(0.038)	(0.057)	(0.035)	(0.039)	(0.043)	(0.055)	(0.047)	(0.043)
$intercept$	0.007	0.018**	0.024	0.056***	0.112***	0.201***	0.266***	0.462***	0.660***
	(0.012)	(0.007)	(0.016)	(0.019)	(0.027)	(0.027)	(0.041)	(0.041)	(0.037)
Obs.	553	553	553	553	553	553	553	553	553
Goodness of fit	0.135	0.189	0.217	0.235	0.236	0.220	0.187	0.150	0.097
t test	-145.990***	-76.545***	-21.200***	1.156	/	-9.684***	-29.751***	-75.374***	-150.970***

Panel B: Crude oil q_o

Variable	Quantile Estimates								
	$q_o = 0.1$	$q_o = 0.2$	$q_o = 0.3$	$q_o = 0.4$	$q_o = 0.5$	$q_o = 0.6$	$q_o = 0.7$	$q_o = 0.8$	$q_o = 0.9$
q_c	0.141***	0.229***	0.286***	0.286***	0.277***	0.227***	0.193***	0.174***	0.043
	(0.044)	(0.060)	(0.072)	(0.061)	(0.086)	(0.077)	(0.065)	(0.041)	(0.049)
$intercept$	0.040*	0.107***	0.166***	0.254***	0.350***	0.492***	0.606***	0.699***	0.870***
	(0.021)	(0.026)	(0.042)	(0.030)	(0.058)	(0.046)	(0.040)	(0.031)	(0.037)
Obs.	553	553	553	553	553	553	553	553	553
Goodness of fit	0.021	0.031	0.030	0.026	0.020	0.015	0.014	0.014	0.001
t test	-37.818***	-18.149***	-6.643***	0.684	/	-8.846***	-17.601***	-25.974***	-46.407***

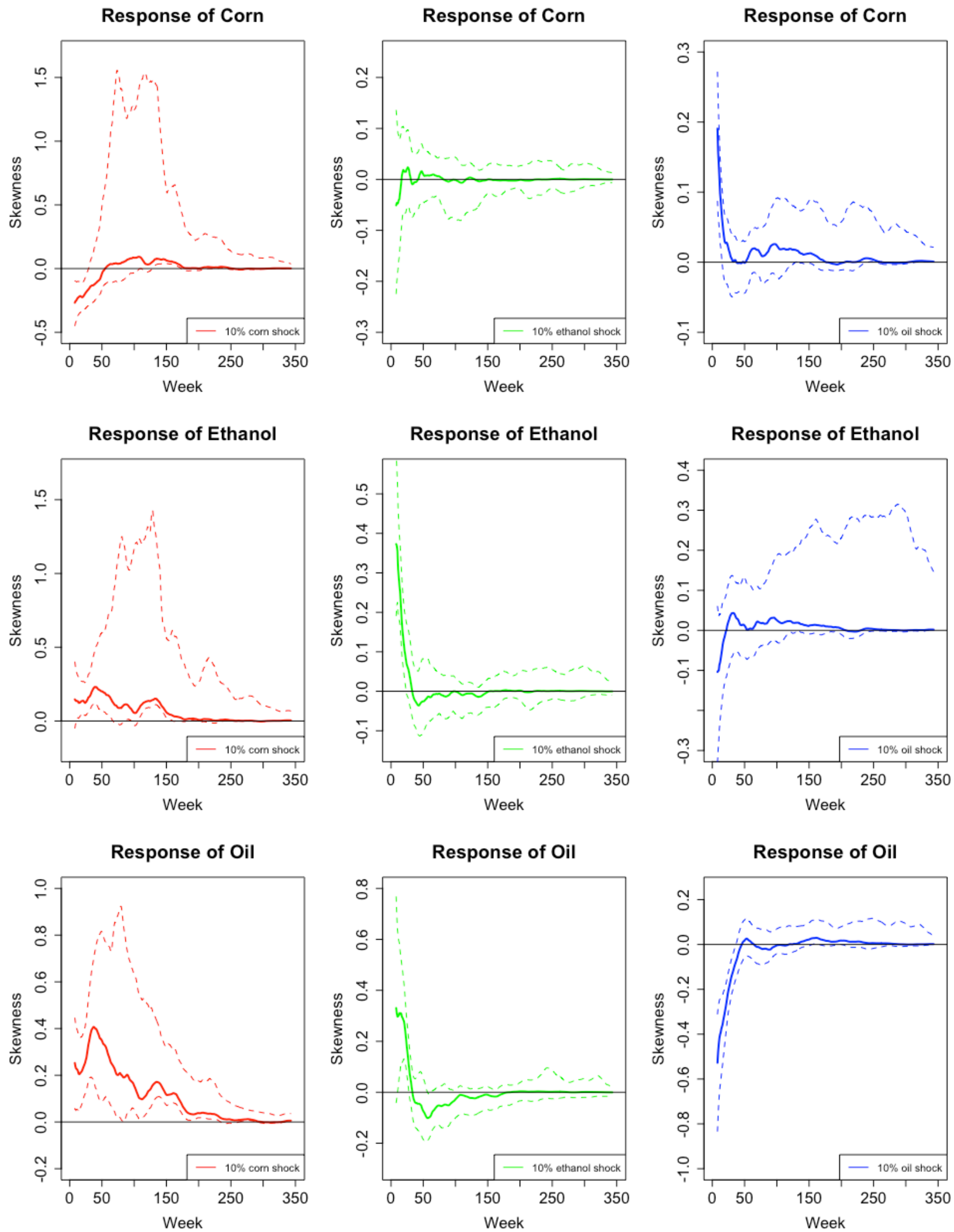
Note: Standard errors are presented in parentheses; they are obtained using bootstrapping. *, **, and *** indicate significant at the 10%, 5%, and 1% significance levels, respectively. For the "goodness of fit", we report the Pseudo-R^2 proposed by Koenker and Machado (1999) for quantile estimates. The t test presents the ratio of the difference of parameter β of other eight quantiles to the median (i.e., q=0.5) using bootstrapping.

Figure B1. Dynamic responses on price mean and standard deviation, conditional on ethanol q_e



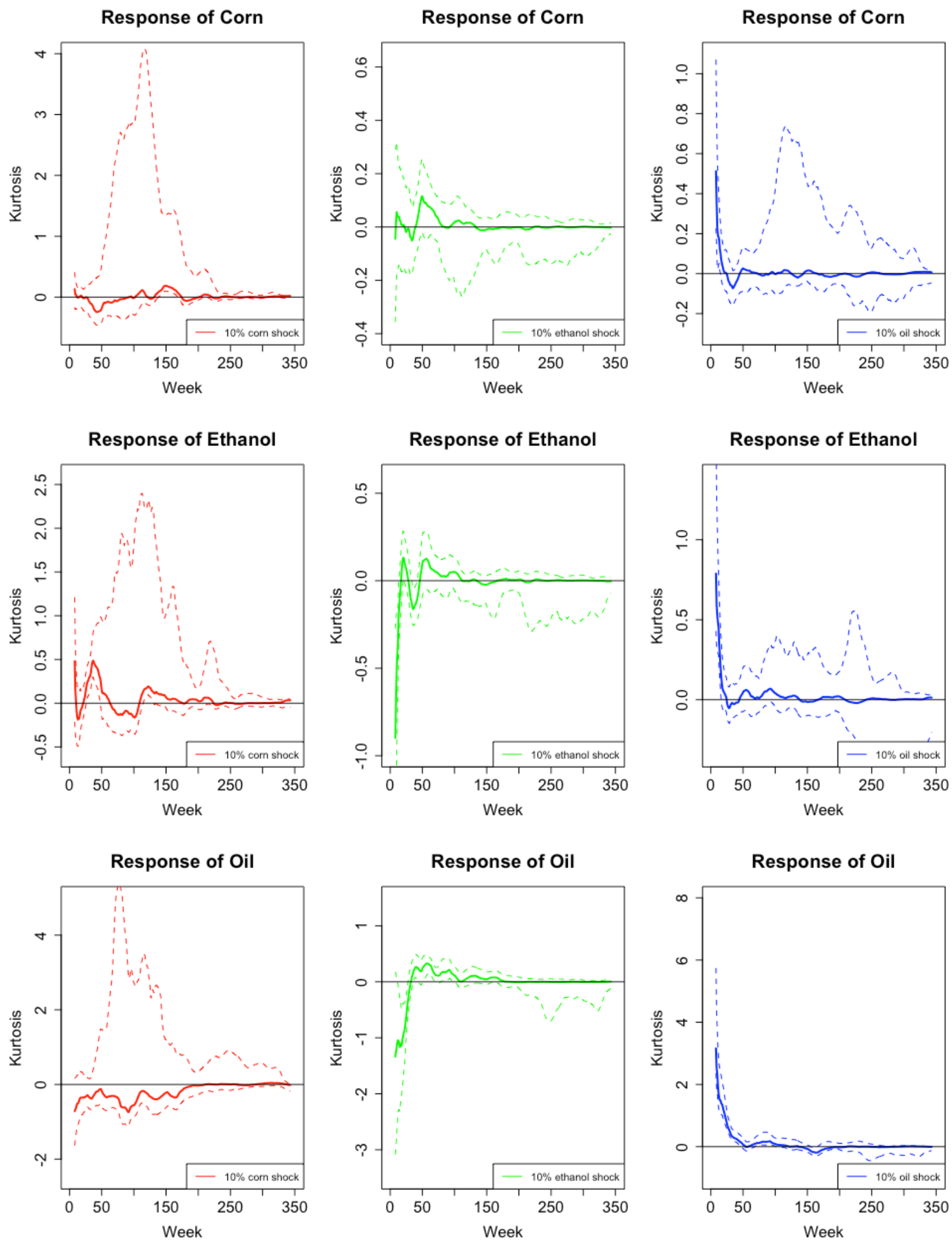
Note: The solid lines show the estimated impulse responses. The dotted lines report the 90% confidence intervals. Take the first graph on the top left for an example, it presents dynamic responses of price mean of corn market following a positive 10% shock to each of three markets, where the red line represents shocks originating from corn market, the green one represents ethanol shocks, and the blue one represents oil shocks.

Figure B2. Dynamic responses on price skewness, conditional on ethanol q_e



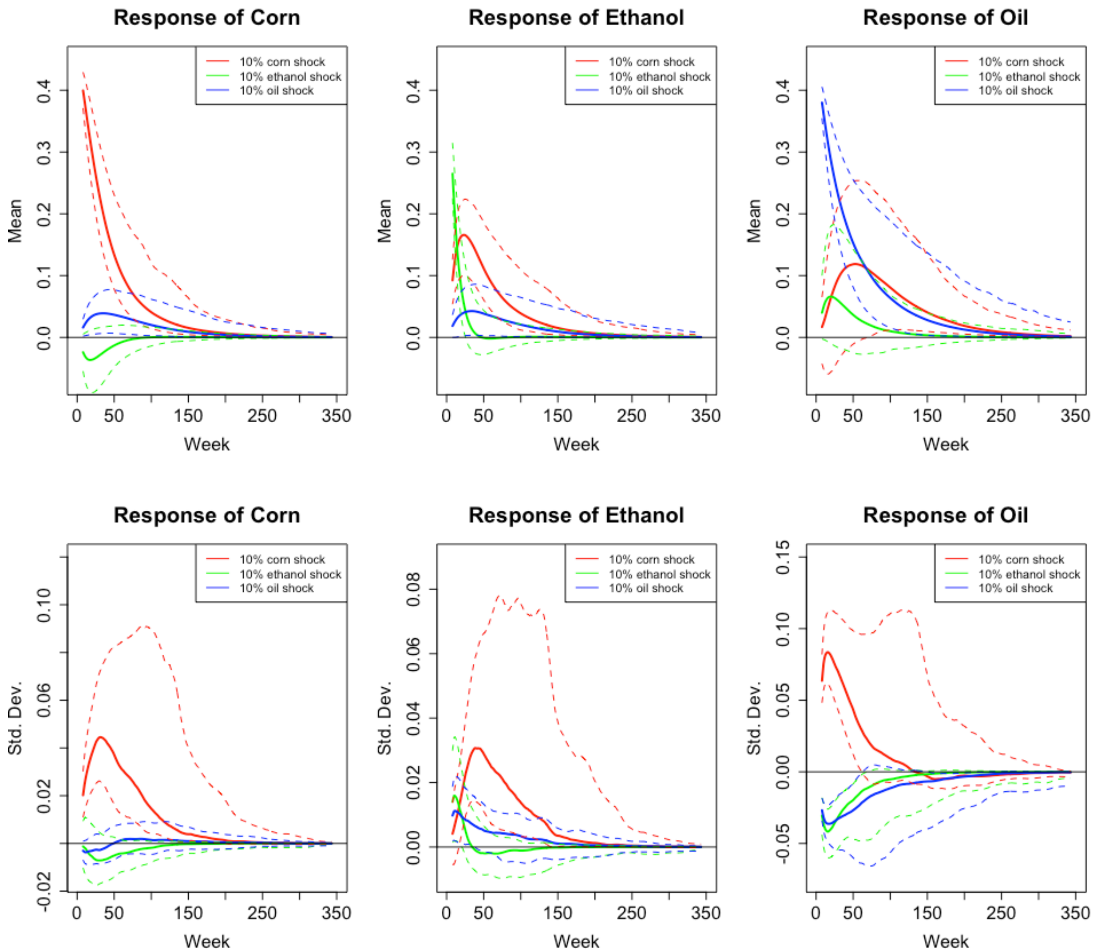
Note: The solid lines show the estimated impulse responses. The dotted lines report the 90% confidence intervals. Take the first graph on the top left for an example, the red line presents dynamic responses of price skewness of corn market following a positive 10% shock to own market (i.e., corn market).

Figure B3. Dynamic responses on price kurtosis, conditional on ethanol q_e



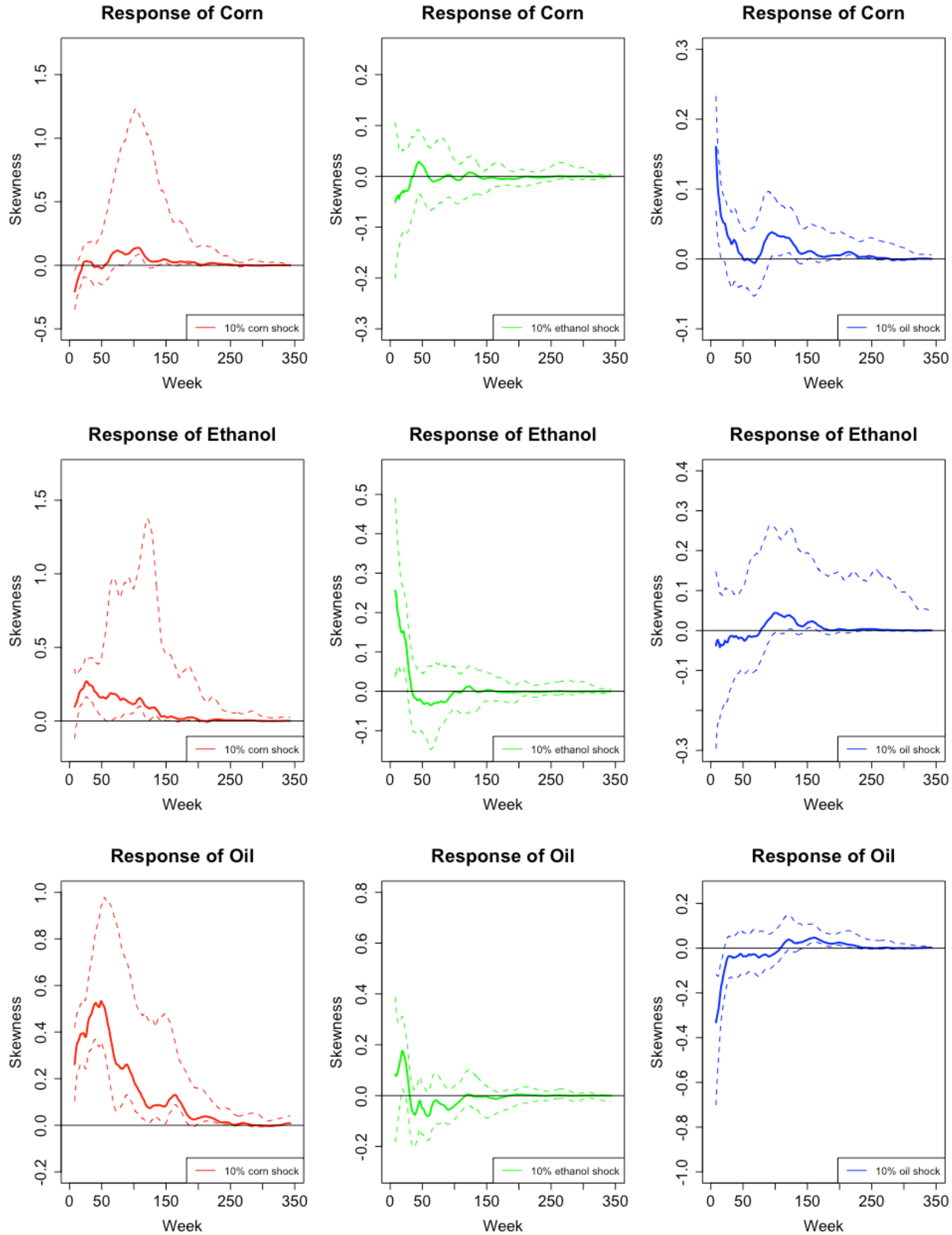
Note: The solid lines show the estimated impulse responses. The dotted lines report the 90% confidence intervals. Take the first graph on the top left for an example, the red line presents dynamic responses of price kurtosis of corn market following a positive 10% shock to own market (i.e., corn market).

Figure B4. Dynamic responses on price mean and standard deviation, conditional on corn q_c



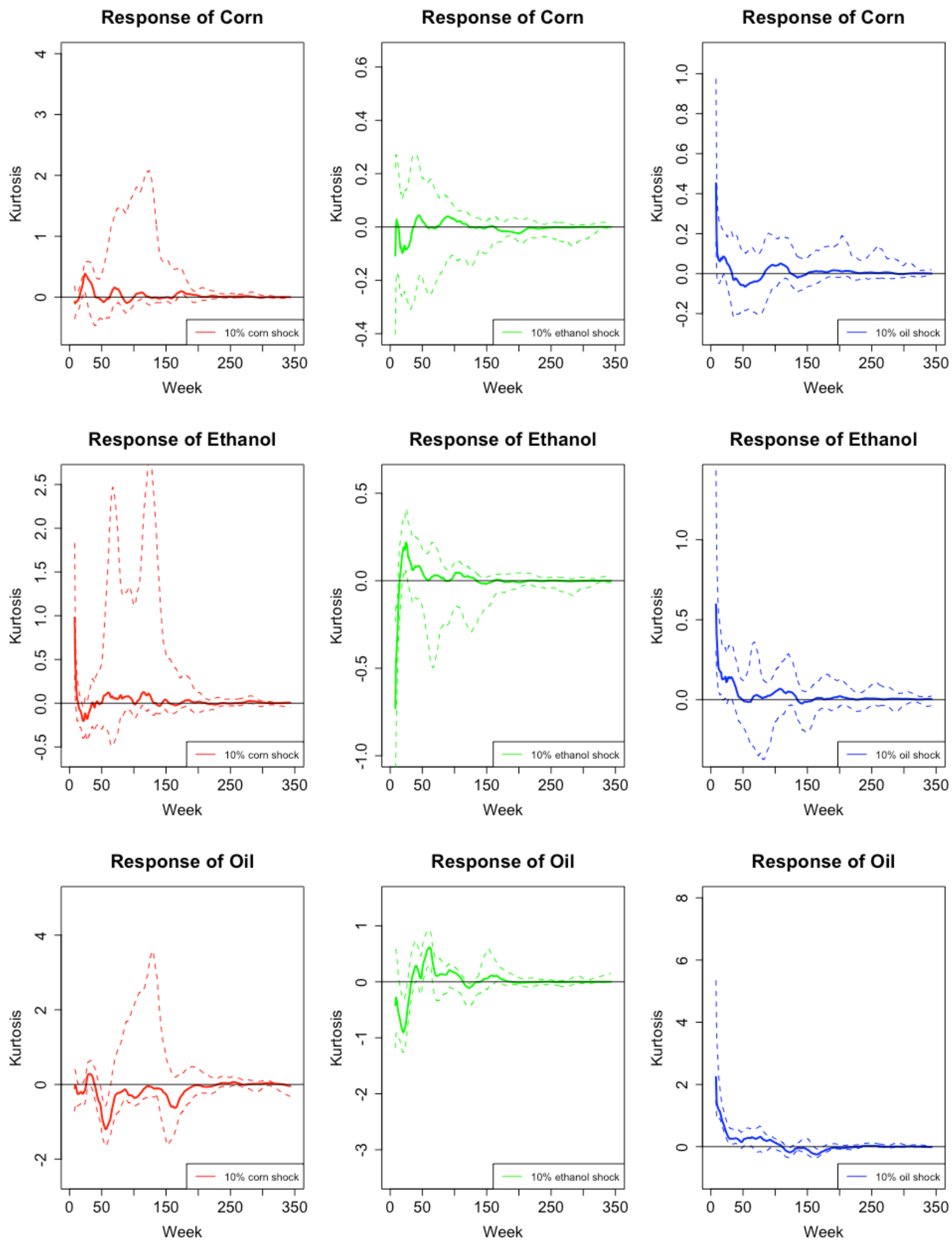
Note: The solid lines show the estimated impulse responses. The dotted lines report the 90% confidence intervals. Take the first graph on the top left for an example, it presents dynamic responses of price mean of corn market following a positive 10% shock to each of three markets, where the red line represents shocks originating from corn market, the green one represents ethanol shocks, and the blue one represents oil shocks.

Figure B5. Dynamic responses on price skewness, conditional on corn q_c



Note: The solid lines show the estimated impulse responses. The dotted lines report the 90% confidence intervals. Take the first graph on the top left for an example, the red line presents dynamic responses of price skewness of corn market following a positive 10% shock to own market (i.e., corn market).

Figure B6. Dynamic responses on price kurtosis, conditional on corn q_c



Note: The solid lines show the estimated impulse responses. The dotted lines report the 90% confidence intervals. Take the first graph on the top left for an example, the red line presents dynamic responses of price kurtosis of corn market following a positive 10% shock to own market (i.e., corn market).

Appendix C: Modulus of the dominant roots $|\lambda_1|$ under alternative P_{t-1} scenarios

Table C1. Estimated modulus of the dominant root $|\lambda_1|$, at low P_{t-1} prices scenario.

$|\lambda_1[(q_c = 0.1, q_e, q_o), \boldsymbol{P}_{t-1}]|$					
q_o \ q_e	0.1	0.3	0.5	0.7	0.9
0.1	1.294***	1.292***	1.302***	1.316***	1.315***
0.3	1.055	1.054	1.056	1.064	1.063
0.5	0.986	0.988	0.986	0.970	0.968
0.7	0.947	0.950	0.949	0.960	0.948
0.9	0.901	0.901	0.873	0.975	0.940
$|\lambda_1[(q_c = 0.5, q_e, q_o), \boldsymbol{P}_{t-1}]|$					
q_o \ q_e	0.1	0.3	0.5	0.7	0.9
0.1	1.301***	1.299***	1.308***	1.321***	1.320***
0.3	1.058	1.057	1.059	1.064	1.064
0.5	0.988	0.990	0.987	1.002	0.992
0.7	0.988	0.990	0.987	1.002	0.987
0.9	0.988	0.988	0.986	1.005	0.987
$|\lambda_1[(q_c = 0.9, q_e, q_o), \boldsymbol{P}_{t-1}]|$					
q_o \ q_e	0.1	0.3	0.5	0.7	0.9
0.1	1.298***	1.295***	1.307***	1.322***	1.322***
0.3	1.054	1.053	1.056	1.066	1.065
0.5	0.994	0.995	0.993	0.970	0.974
0.7	0.981	0.98	0.982	0.964	0.983
0.9	0.981	0.98	0.982	0.970	0.983

Note: The reported modulus of the dominant root $|\lambda_1|$ are evaluated at 0.25 sample quantiles. Testing the null hypothesis H_0: $|\lambda_1| \leq 1$, statistical significance of (local) instability is denoted by stars: *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively.

Table C2. Estimated modulus of the dominant root $|\lambda_1|$, at high $\boldsymbol{P}_{t-1}$ prices scenario.

q_o \ q_e	0.1	0.3	0.5	0.7	0.9
			$\lvert\lambda_1[(q_c = 0.1, q_e, q_o), \boldsymbol{P}_{t-1}]\rvert$		
0.1	1.068	1.061	1.081	1.060	1.071
0.3	1.030	1.029	1.031	1.025	1.028
0.5	0.993	0.994	0.993	1.008	1.001
0.7	0.996	0.998	0.996	1.012	1.006
0.9	1.013	1.011	1.015	1.005	0.997
			$\lvert\lambda_1[(q_c = 0.5, q_e, q_o), \boldsymbol{P}_{t-1}]\rvert$		
q_o \ q_e	0.1	0.3	0.5	0.7	0.9
0.1	1.095	1.090	1.103	1.091*	1.098*
0.3	1.037	1.037	1.038	1.033	1.036
0.5	0.988	0.990	0.987	1.009	0.998
0.7	0.992	0.994	0.991	1.018	1.000
0.9	0.997	0.997	0.997	1.010	1.002
			$\lvert\lambda_1[(q_c = 0.9, q_e, q_o), \boldsymbol{P}_{t-1}]\rvert$		
q_o \ q_e	0.1	0.3	0.5	0.7	0.9
0.1	1.077	1.067	1.094	1.068	1.083
0.3	1.031	1.030	1.034	1.023	1.026
0.5	0.994	0.995	0.993	1.007	1.006
0.7	0.996	0.998	0.996	1.009	1.007
0.9	1.011	1.011	1.012	1.010	1.011

Note: The reported modulus of the dominant root $|\lambda_1|$ are evaluated at 0.75 sample quantiles. Testing the null hypothesis H_0: $|\lambda_1| \leq 1$, statistical significance of (local) instability is denoted by stars: *, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively.

Appendix D: Robustness check on volatility impulse response with GARCH-BEKK model

Table D1. Estimates of the VAR for returns of corn, ethanol and crude oil

Variable	r^c	r^e	r^o
r^c_{t-1}	0.038	0.096*	-0.011
	(0.047)	(0.054)	(0.084)
r^e_{t-1}	-0.041	-0.043	-0.045
	(0.043)	(0.049)	(0.077)
r^o_{t-1}	0.029	0.039	0.078*
	(0.025)	(0.029)	(0.045)
$Intercept$	-0.020	-0.064	0.038
	(0.030)	(0.034)	(0.053)
Obs.	553	553	553
Goodness of fit	0.004	0.009	0.006

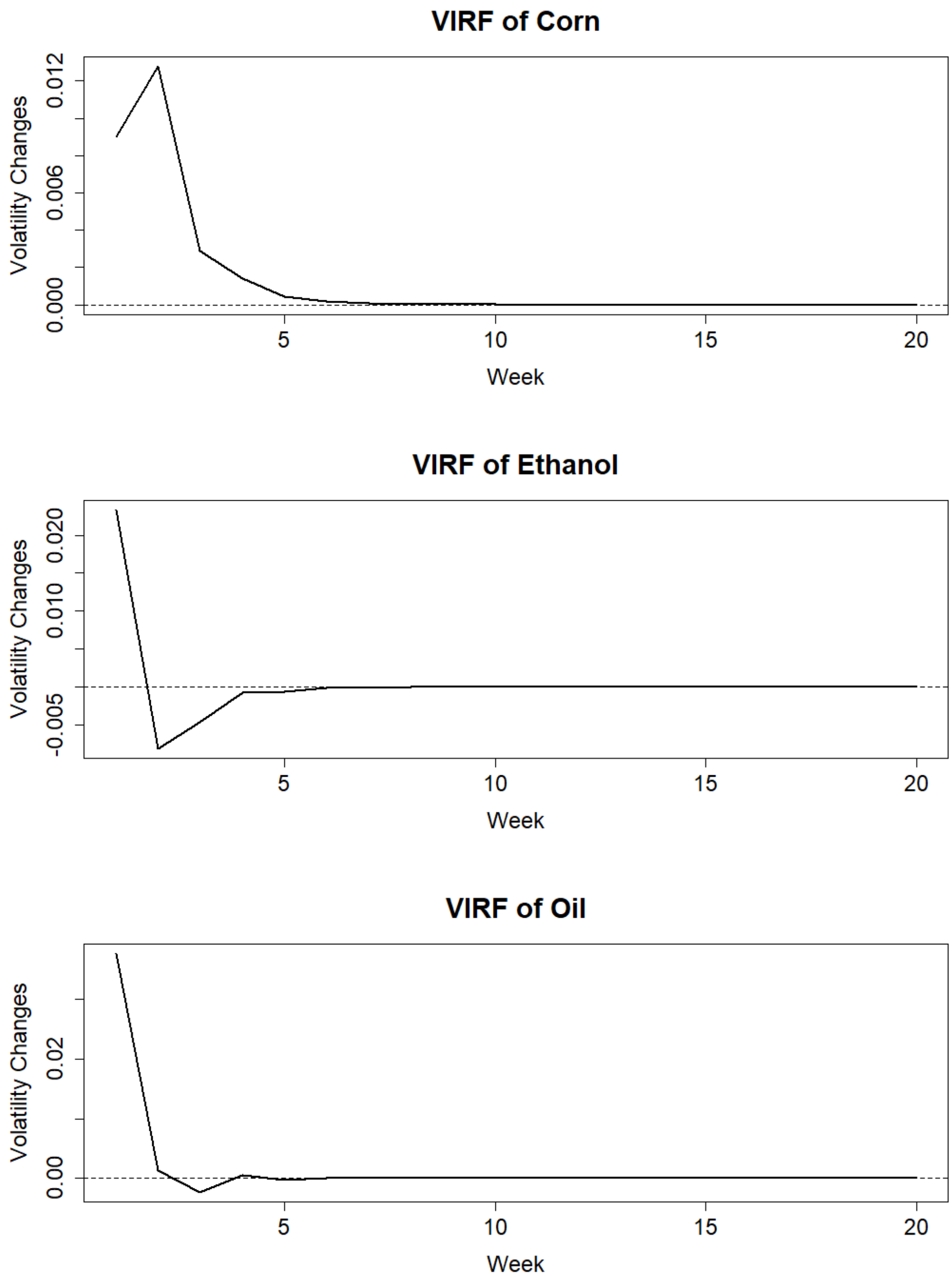
Note: Standard errors (presented in parentheses) are obtained using bootstrapping. *, **, and *** indicate significant at the 10%, 5%, and 1% significance levels, respectively. For the "goodness of fit", we report the adjusted R^2 for VAR estimates.

Table D2. Estimates of GARCH-BEKK (1, 1) model for corn, ethanol, and crude oil futures returns

Variable	r^c	r^e	r^o
c_1	0.405***	0.216***	0.064
	(0.047)	(0.038)	(0.063)
c_2	0.000	-0.007	0.000
		(0.205)	(0.087)
c_3	0.000	0.000	-0.001
			(0.086)
α_1	0.684***	-0.041	0.165***
	(0.061)	(0.058)	(0.060)
α_2	-0.066	0.452***	0.096*
	(0.049)	(0.066)	(0.050)
α_3	-0.037*	0.052***	0.190***
	(0.020)	(0.018)	(0.033)
g_1	0.550***	-0.007	0.422***
	(0.085)	(0.047)	(0.127)
g_2	0.013	0.901***	0.133
	(0.033)	(0.030)	(0.156)
g_3	0.030	-0.190***	-0.985***
	(0.046)	(0.066)	(0.020)
	1.409	1.090	1.065
λ_i	0.954	0.833	0.622
	0.547	0.390	0.288

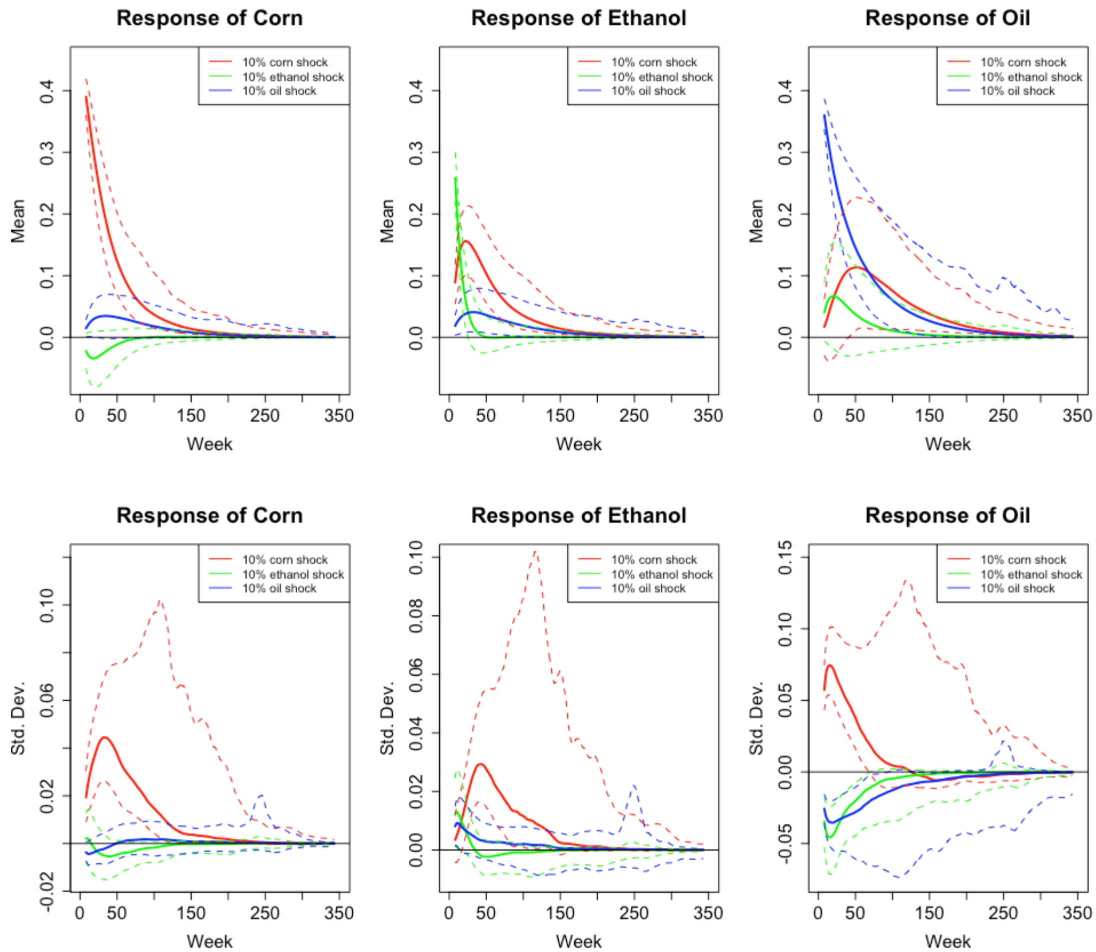
Note: The λ_i are the eigenvalues of the matrix A11⊗A11+G11⊗G11. Standard errors are presented in parentheses; they are obtained using bootstrapping. *, **, and *** indicate significant at the 10%, 5%, and 1% significance levels, respectively.

Figure D1. Volatility impulse response function with GARCH-BEKK (1,1) model



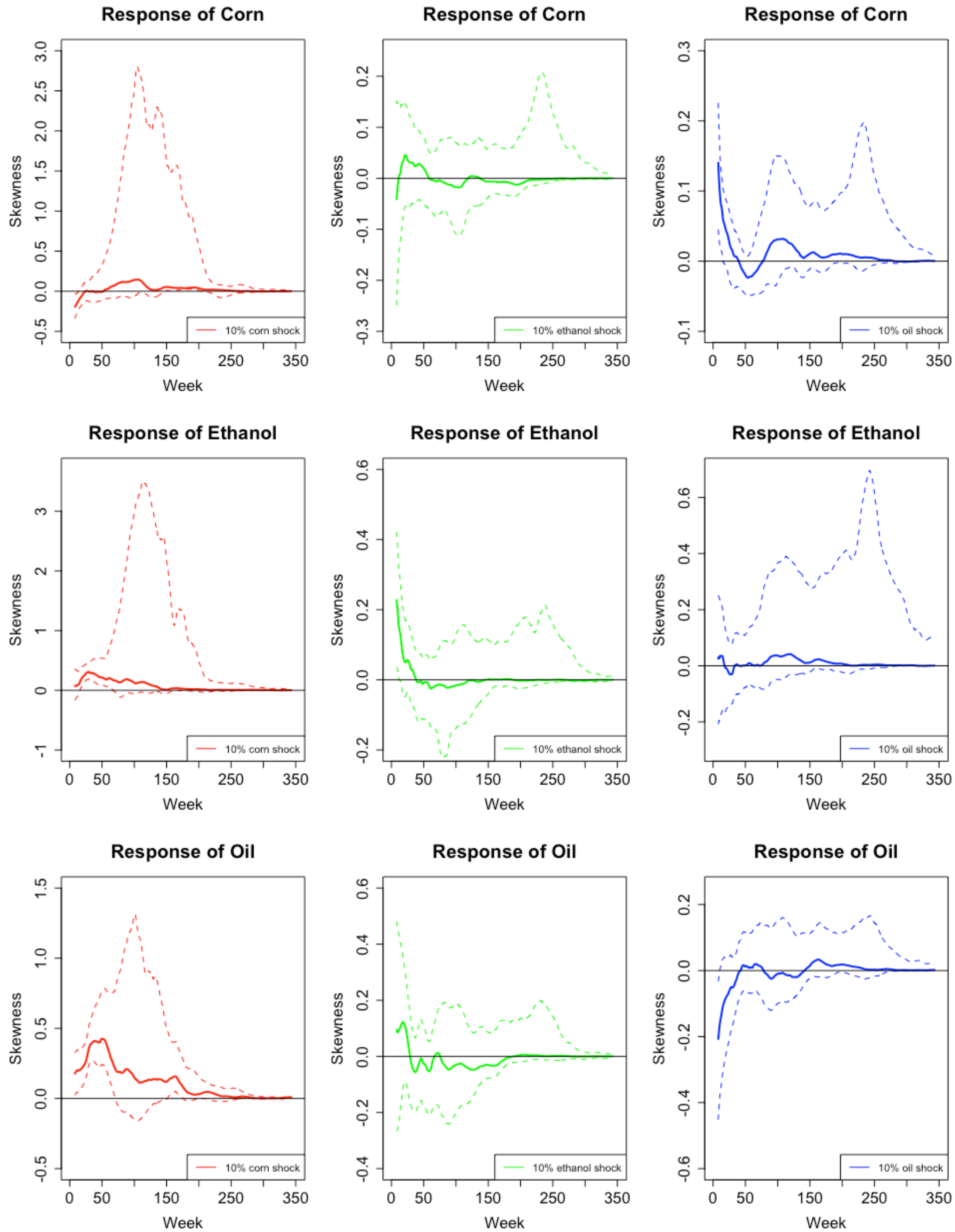
Appendix E: Robustness check on initial conditions in dynamic response simulations

Figure E1. Dynamic responses on price mean and standard deviation, conditional on crude oil, under lower price scenario (0.3 quantile)



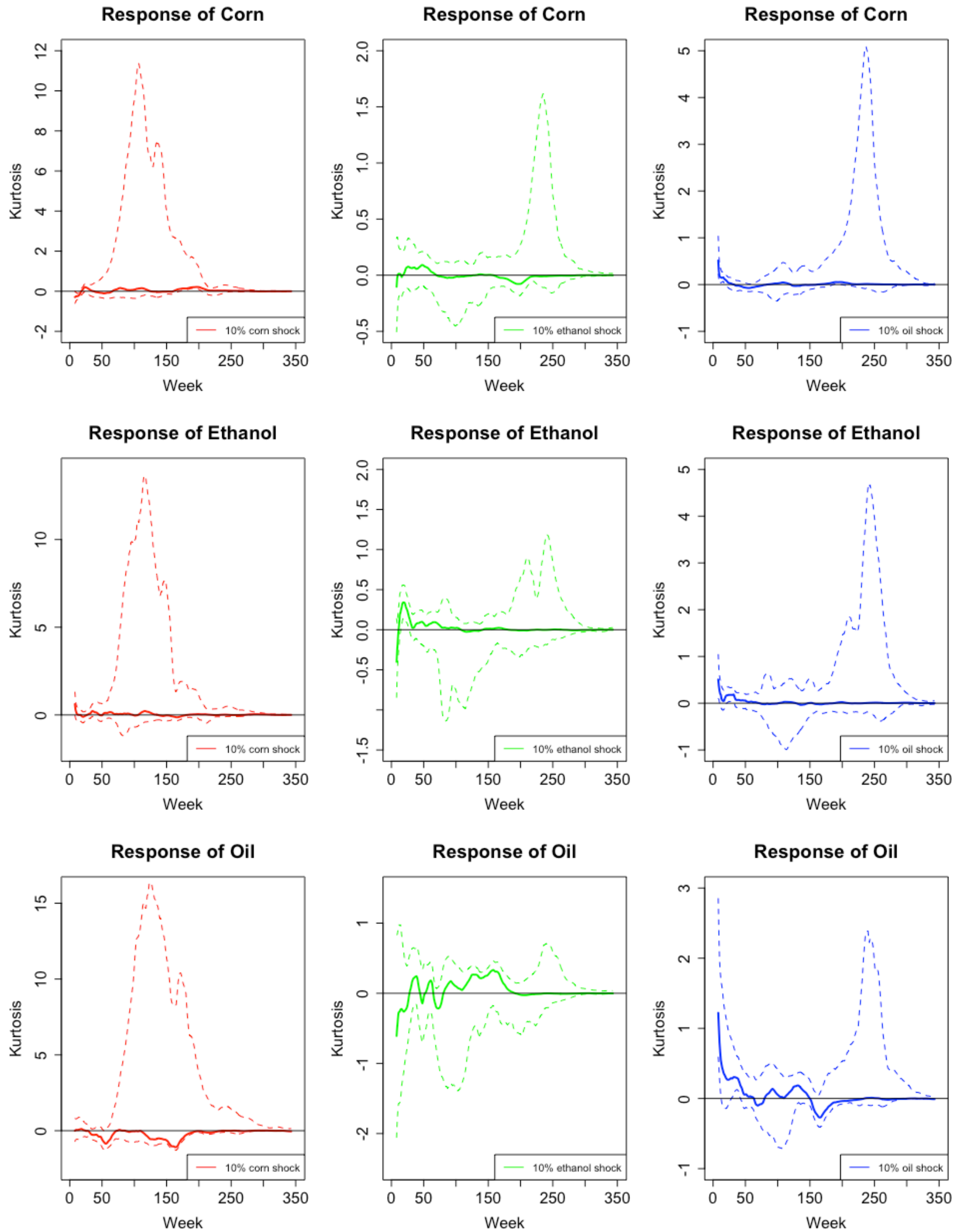
Note: The solid lines show the estimated impulse responses. The dotted lines report the 90% confidence intervals. Take the first graph on the top left for an example, it presents dynamic responses of price mean of corn market following a positive 10% shock to each of three markets, where the red line represents shocks originating from corn market, the green one represents ethanol shocks, and the blue one represents oil shocks.

Figure E2. Dynamic responses on price skewness, conditional on crude oil, under lower price scenario (0.3 quantile)



Note: The solid lines show the estimated impulse responses. The dotted lines report the 90% confidence intervals. Take the first graph on the top left for an example, the red line presents dynamic responses of price skewness of corn market following a positive 10% shock to own market (i.e., corn market).

Figure E3. Dynamic responses on price kurtosis, conditional on crude oil, under lower price scenario (0.3 quantile)



Note: The solid lines show the estimated impulse responses. The dotted lines report the 90% confidence intervals. Take the first graph on the top left for an example, the red line presents dynamic responses of price kurtosis of corn market following a positive 10% shock to own market (i.e., corn market).

Footnotes

[1] Serra & Zilberman (2013) and Hochman & Zilberman (2018) had nice reviews of the literature on the biofuel-related price transmission and volatility spillovers for the agricultural and energy markets in the long-term and as well as short-term, with focuses on mainly three commodities—corn, ethanol, and crude oil.

[2] For example, GARCH models have been proposed to explore the dynamics of both mean and variance (e.g., Engle, 1982; Bollerslev, 1986; Bauwens et al., 2006). And the role of nonlinearity has been examined in time series models (e.g., Hamilton, 1989; Tong, 1990; Teräsvirta, 1994). As discussed below, our analysis is more general in the sense that it goes beyond a moment-based approach and applies to the dynamics of a multivariate distribution.

[3] One proposed approach has been to decompose a bivariate distribution and estimate the associated marginal and conditional distributions (Wei, 2008). But a focus on two stochastic variables is restrictive. Another line of inquiry has been to rely on depth functions (Breckling et al., 2001; Hallin et al., 2010; Kong & Mizera, 2012; Chakraborty & Chaudhuri, 2014). But depth-based methods fail to deal with nonconvexity that can arise in multivariate quantiles; and addressing this issue makes the estimation more difficult (Chernozhukov et al., 2017; Chavas, 2018; Carlier et al., 2022; Ghosal & Sen, 2022). As discussed below, our proposed approach is more general in the sense that it applies to a multivariate distribution, and it allows for both cross-market dynamics and contemporaneous codependence.

[4] Applied to dynamic models, impulse response functions can be used to assess the dynamic impact of any specific shock (e.g., Hamilton, 1994; Potter, 2000; Enders, 2010; Plagborg-Møller & Wolf, 2021). Impulse response functions have been commonly evaluated in the context of Vector Autoregression (VAR) models, where they have the disadvantage of being sensitive to the order of the equations (Hamilton, 1994, p. 322-323). This problem can also arise in quantile models (e.g., White et al., 2015; Lee et al., 2021). Noting that there is no “error term” in quantile models, our proposed evaluation of

dynamic adjustments is based on changes in initial conditions. In this context, our impulse response function analysis is not sensitive to the ordering of the equations (as discussed below).

[5] A structural model associated with (1) is given by the market equilibrium conditions $\sum_{j \in M_{it}} y_{ij}(\boldsymbol{p}_t, \cdot) = 0$, where $y_{ij}(\boldsymbol{p}_t, \cdot)$ is the net trade (defined as positive for a seller and negative for a buyer) provided by the j-th trader in the i-th market at time t, M_{it} denoting the corresponding set of traders, $i \in N$. Then, equation (1) is the solution of this system of equations for $\boldsymbol{p}_t$.

[6] Under contemporaneous independence, the copula would satisfy $C(F_1, \ldots, F_n) = \prod_{i \in N} F_i$. Alternatively, having $C(F_1, \ldots, F_n) \neq \prod_{i \in N} F_i$ would imply the presence of contemporaneous codependence across prices. Alternative measures of codependence have been proposed in the literature (e.g., Joe, 2015; Nelsen, 2006). One of these measures is the Spearman's rank correlation $\rho_{ij} = cor[F_i, F_j] \in [-1, 1],\ i, j \in N$.

[7] From equation (7), note that the bivariate copula $C_{ki}(q_k, q_i)$ can be obtained from $C_{i|k}(q_i|q_k)$ as: $C_{ki}(q_k, q_i) = \int_0^{q_k} C_{i|k}(q_i|\bar{q}_k)\, d\bar{q}_k$. The copula $C_{ki}(q_k, q_i)$ being unique, it follows that the evaluation of codependence between i and k (as captured by the bivariate copula $C_{ki}(q_k, q_i)$) would remain the same (asymptotically) if we were to switch i and k in (7). In other words, the evaluation of codependence between i and k is expected to be (asymptotically) invariant to the choice of the conditioning variable in equation (7). We checked this property in our empirical analysis.

[8] Note that equation (8) restricts the coefficient of q_k to vary only with q_i. Extending the model to allow the marginal effect of q_k to vary also with q_k can be done easily by letting $c_{1k}(q_i) = c_{1k}(q_i) + c_{2k}(q_i)\, q_k$. We explored this option in the empirical analysis presented in section 4, but we found that the coefficients $c_{2k}(q_i)$ were not statistically significant.

[9] As noted in footnote 2, there is no "error term" in our quantile approach. Thus, we cannot evaluate dynamic adjustments based on changes in "error terms" (as is typically done in the estimation of impulse response functions using VAR models (Hamilton, 1994, p. 320-323)). This motivates us to focus our evaluation of dynamic multipliers based on changes in initial conditions $\boldsymbol{P}_{0s}$. Importantly, this avoids the issue arising in VAR models where impulse response functions depend (under non-zero covariances) on the order of the equations (Hamilton, 1994, p. 322).

[10] Data available at: U.S. Department of Agriculture, Economic Research Service, Biofuel Data Sources. Https://www.ers.usda.gov/about-ers/partnerships/strengthening-statistics-through-the-icars/ biofuels-data-sources/.

[11] Data available at: U.S. Energy Information Administration, 2022 Fuel Ethanol Production Capacity. https://www.eia.gov/todayinenergy/detail.php?id=53539

[12] The selection of the sample period (2010-2020) is motivated by data availability and an attempt to avoid the market turmoil associated with the 2007-2008 financial crisis.

[13] The time trend included the QVAR specifications is a continuous variable, $tt = (1, 2, \dots, 552, 553)/100$.

[14] More than 80 model specifications of food-fuel dynamics were evaluated. The BIC evaluation results are available from the authors upon request.

[15] For comparison, the estimates of a conventional VAR model applied to a similar specification are reported in Appendix A.

[16] In Tables 2-4, the own lagged price coefficients would measure the dynamic effect of $p_{i,t-1}$ on $p_{i,t}$ in the absence of nonlinear dynamics. As discussed below, in the presence of nonlinear dynamics, these coefficients provide only a partial measure of lagged price effects.

[17] The copula estimation was also conducted by switching the conditionality from the oil price to the ethanol price or the corn price. The results are reported in Appendix B. In a way consistent with the discussion presented in footnote 5, the estimated results were found to be robust.

[18] Such argument also means that industries would have few incentives to prevent price spikes in their output market (as they benefit from higher output prices), indicating that the presence of local instability is more likely to occur in the upper tail of the price distribution in output markets (e.g., as found Chavas & Li, 2020).

[19] This includes using the bootstrapped distribution to test the null hypothesis that dynamic responses are not different from zero: H_0: $M_{jit}^{e}(\boldsymbol{P}_0) - M_{jit}^{e}(\boldsymbol{P}_{0s}) = 0$.

[20] The lines reported in Figures 2-4 were smoothed using five-point moving-average function. So were the lines in the Figures reported in Appendix B and E.

[21] We also evaluated different confidence intervals from the bootstrapped distribution (e.g., 95% confidence interval). The results are available from the authors upon request.

[22] Additional robustness checks are presented in Appendix D (presenting results from a GARCH model) and Appendix E (reporting estimates obtained from using alternative price scenarios).