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Food–oil volatility spillovers and the impact of distinct biofuel policies on price uncertainties on feedstock markets

Helmut Herwartz | **Alberto Saucedo**

Faculty of Economics, Chair of Econometrics, University of Göttingen, Humboldtallee 3, Göttingen, Germany

Correspondence
Alberto Saucedo, Faculty of Economics, Chair of Econometrics, University of Göttingen, Humboldtallee 3, D-37073 Göttingen, Germany.
Email: saucedo.publications@gmail.com

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Abstract

Over recent decades, the link between crude oil and agricultural markets has been reinforced following the introduction of biofuels. We use timely measures of (co)variation spillovers to analyze the role of crude oil in shaping price uncertainties of agricultural commodities, which are largely used as biofuel feedstocks. Our sectoral- and market-specific measures distinguish tranquil (1995–2005) and crisis episodes (2006–2015), as well as periods during which either consumption mandates or tax credits were enacted to spur biofuels. During the crisis period, crude oil volatility transmissions account for 16% (20%) of price uncertainties in ethanol (biodiesel) feedstock markets on average. Moreover, we find evidence of enhanced volatility transmissions under tax credit regimes compared with consumption mandates. The results from pooled regressions confirm stronger volatility transmissions by about 12% under the enactment of tax credits.

KEYWORDS
biofuel mandates and tax credits, commodity markets, multivariate GARCH, volatility spillovers

JEL CLASSIFICATION
C32, C58, Q02, Q16, Q18

1 | INTRODUCTION

Periods of high price uncertainty on staple food markets—like those observed during the food crisis of 2006 and after the financial crash of 2008—have led to considerable private and social costs. Developing countries are particularly vulnerable to food price volatility, as food expenditures represent a major budget share for most of their populations. Additionally, increased uncertainty on feedstock markets might discourage investments in agriculture, which could in turn threaten food security in the medium term by reducing food availability and increasing nourishment costs. In sum, pertinent food price volatility potentially leads to social unrest and political instability (FAO et al., 2011; Prakash, 2011). Although the existing literature attributes the increasing volatility of agricultural prices to different factors and their interactions, there is a special interest in the effects of crude oil price changes on agricultural markets.[1]

The literature on volatility spillovers between crude oil and food markets has been growing since the early-2000s. Most articles assess correlations or causalities in the Granger sense (e.g., Busse, Brümmer, & Ihle, 2011; Harri & Hudson, 2009; Mensi, Hammoudeh, Nguyen, & Yoon, 2014;

[1] For a review of potential determinants of price volatility on agricultural markets, see, for example, Brümmer, Korn, Schlüssler, Jaghdani, and Saucedo (2013).

Nazlioglu, Erdem, & Soytas, 2013), while others focus on inferential diagnostics retrieved from cross-market volatility specifications (e.g., Alom, Ward, & Hu, 2011; Serra, Zilberman, Gil, & Goodwin, 2011; Wu & Li, 2013). To the best of our knowledge, Wu, Guan, and Myers (2011) and Trujillo-Barrera, Mallory, and Garcia (2012) are exceptional in providing model-implied measures of volatility spillovers from crude oil to agricultural products. The linkage between oil and agricultural commodities was traditionally determined by using oil derivatives as inputs for crop production, processing, and transporting. Despite being close substitutes for fossil fuels (i.e., gasoline and diesel), relatively high production costs imply that biofuels derived from cereals, sugar crops, and oilseeds only scarcely compete with their fossil counterparts. Consequently, without adequate subsidy-like supporting measures, they are driven out of competitive markets such as that for transport fuels. Against this background, ambitious policies have boosted biofuel output and provoked unintended consequences in agricultural markets, such as reducing per capita food availability, price runs, and augmented price uncertainty of staple foods (Wright, 2014).[2] Policies to foster the use and production of biofuels include blending mandates and tax exemptions. Additionally, governments have intervened by means of subsidizing feedstock production factors (labor, capital, land) or offering releases to final products (de Gorter, Drabik, Just, & Kliauga, 2013; Sorda, Banse, & Kemfert, 2010). While mandates oblige consumers to use a certain portion of biofuels mixed with fossil fuels (gasoline and diesel), tax credits are duty relieves gained by blenders for units of biofuel that they mix with gasoline or diesel. As a result of policy interventions, biofuels start to follow price dynamics of crude oil and their derivatives markets. Focusing on first-order price linkages among feedstocks, biofuels, and crude oil, de Gorter, Drabik, and Just (2015) ascertain that during periods when blending requirements govern the price discovery of biofuels, their feedstock prices primarily follow the dynamics on agricultural markets. However, if tax credits are binding,[3] feedstock markets are more subjected to price discoveries on crude oil markets.

The objectives of this article are twofold. In the first instance, we aim at the provision of flexible dynamic measures that summarize directional (co)variation flows with high time resolution and at distinct scales (singular markets, sectors or entire dynamic systems). In the second instance, we take advantage of suitably defined spillover statistics (a) to quantify pre- and postcrisis vulnerabilities of feedstock markets to crude oil shocks, and (b) analyze the particular effects of two major biofuel policies –tax credits and blending targets—on the intensity of crude oil volatility transmission to major feedstock markets. In order to achieve these purposes, we adopt the volatility spillover indices of Fengler and Herwartz (2018), which are derived from linearized versions of multivariate GARCH (MGARCH) models. By means of daily quotes of crude oil and feedstock prices covering the period from October 1995 until February 2015, we quantify volatility transmission outcomes among grains, sugar, vegetable oils, and crude oil markets. Implemented at high frequency, the adopted framework allows tracing differentiated volatility transmission patterns induced by events at particular time points, such as crisis periods or policy interventions.

Our results suggest that—compared with ethanol feedstocks (corn, wheat, and sugar)—vegetable oil markets (soybean, rapeseed, and palm) are more sensitive to shocks originating in crude oil markets, in particular soybeans with reference to the food crisis of 2006 and the financial turmoil of 2008. Besides financial unrest, uncertainty levels on crude oil markets and policy regimes also exacerbate crude oil volatility spillovers to feedstock markets. In terms of marginal policy-induced volatility receptions, largely traded ethanol feedstocks are more responsive to crude oil markets compared with vegetable oils.

In Section 2, we provide a brief overview of the methodological approaches followed in the related literature and their main findings. In Section 3, we outline how the impacts of (co)variations of crude oil prices on agricultural price uncertainties are assessed in this work. In Section 4, we (a) describe the data, (b) provide magnitudes and directional measures of volatility spillovers, and (c) discuss estimates of the distinguished effects of two major biofuel policies on the transmission of oil (co)variations to agricultural markets. Finally, Section 5 summarizes and concludes.

2 | ECONOMETRIC PERSPECTIVES ON THE FOOD–OIL NEXUS

Having experienced episodes of enhanced food price volatility, the international community has renewed its interest in understanding and managing the sources of uncertainties in agricultural markets. Research on dynamic relations among agricultural and crude oil markets has mainly applied time series econometrics to reveal causalities/correlations. For the parameterization of the conditional mean, vector autoregressive (VAR) or vector error correction models (Engle & Granger, 1987) have been frequently applied, while a few authors have also added exogenous covariates. For instance, Chang and Su (2010) treat crude oil log price changes

[2] Major biofuel policies aim to reduce greenhouse gas emissions, diversify energy sources and foster regional development. The International Energy Agency has estimated the global subsidy costs of biofuels (including consumption mandates) at US$ 1.4 trillion for the period between 2011 and 2035 (Gerasimchuk, Bridle, Beaton, & Charles, 2012).

[3] de Gorter, Drabik, Just, and Kliauga (2013) consider a policy as binding if it determines the price formation of biofuels.

exogenously, whereas Serra and Gil (2012) use forecasts of the corn stock-to-use ratios and interest rate volatility as weakly exogenous explanatory variables in the conditional mean of the model specification. Among available multivariate GARCH (MGARCH) representations,[4] the so-called BEKK specification (Engle & Kroner, 1995) has been frequently applied, since it inherits a rich cross-equation dynamic structure and issues positive definite covariance patterns under mild conditions. Most studies applying MGARCH models document significant parameter estimates pointing to some degree of volatility spillovers originating in crude oil and flowing to agricultural markets (e.g., Alom et al., 2011; Wu & Li, 2013). Similarly, applications of so-called dynamic conditional correlation models (Engle, 2002) often document increased correlations between oil and agricultural products, particularly since 2006 (e.g., Busse et al., 2011; Gardebroek & Hernandez, 2013; Mensi et al., 2014). As an alternative to covariance and correlation models, tests for Granger causality in variance have also prompted the conclusion that oil volatilities are Granger-causal for volatilities in grain markets, especially conditional on recent (i.e., post-2006) sample information (e.g., Harri & Hudson, 2009; Nazlioglu et al., 2013).

Despite highlighting the heterogeneity of econometric treatments of food–oil linkages, our review is far from exhaustive.[5] Nonetheless, it is striking that despite conceptual differences, correlations and Granger causalities are described interchangeably as "volatility spillovers" throughout the literature. As notable exceptions, Wu et al. (2011) and Trujillo-Barrera et al. (2012) derive explicit measures of the total effect of crude oil volatility on agricultural products from implied (co)variance profiles of univariate GARCH and MGARCH models. However, it is not straightforward to extend the framework applied in Wu et al. (2011) or Trujillo-Barrera et al. (2012) to the definition of covariance spillovers, which have recently been found to be important channels of inter-market information flows (Fengler & Gisler, 2015). The spillover measures provided in the next section allow generic definitions of directional (co)variation spillovers.

3 | MONITORING RISK TRANSMISSIONS IN AGRICULTURAL MARKETS

This section first briefly outlines the spot indices of volatility transmission developed in Fengler and Herwartz (2018). Second, we adapt their approach to vector systems of (log) commodity price changes to address food–oil linkages. For this purpose, we (a) determine total and directional indices, and (b) characterize vulnerabilities on aggregated and specific (agricultural) markets. To lay the groundwork for the empirical analysis in Section 4, the concepts and diagnostic tools introduced in this section also take account of market characteristics and specific events covered by the sample period. We separate the agricultural commodities according to their suitability for either ethanol or biodiesel processing. The ethanol group comprises crude oil, corn, wheat, and sugar, while the biodiesel group comprises crude oil, soybean oil, rapeseed oil, and palm oil. The inclusion of crude oil in both groups allows us to quantify food–oil (co)variation dynamics. Regarding the sample period, our analysis takes account of major events in agricultural markets after 2005.[6] Accordingly, our descriptive analysis of data and model implications differentiates between two subperiods, namely October 1995-December 2005 (precrisis, Period I) and January 2006-February 2015 (crisis, Period II).

3.1 | Measuring volatility spillovers with high time resolution

3.1.1 | Forecast error variance decompositions

Among rival assessments of risk transmission on speculative markets, the spillover indices of Diebold and Yilmaz (2009, 2014) are unique in showing a rather close relation to standard diagnostics known from the VAR literature (Lütkepohl, 2007). These statistics are essentially forecast error variance decompositions (FEVDs) derived from VAR models of realized volatilities. However, in terms of analyzing market interrelations at high frequency, the spillover indices of Diebold and Yilmaz (2009) are limited in scope as they build upon the assumption of dynamically stable VARs over extended time periods. Motivated by an interest in timely assessments of market interdependencies and building upon traditional FEVDs, Fengler and Herwartz (2018) propose measures of volatility propagation (transmission and reception) from the vector ARMA representation of a squared MGARCH process (comprising both squared returns and return cross products). Focusing on the BEKK variant of MGARCH models, we next turn to a brief description of the volatility spillover statistics in Fengler and Herwartz (2018).

3.1.2 | FEVDs in linearized MGARCH models

Specified in an empirically relevant and parsimonious form, a BEKK(1,1) model for K-dimensional vector valued log price changes, $r_t = (r_{1t}, r_{2t}, \ldots, r_{Kt})'$, reads as

$$r_t = \mu_t + \varepsilon_t = \mu_t + H_t^{1/2}\xi_t \tag{1}$$

[4] See Bauwens, Laurent, and Rombouts (2006) for a review treatment of multivariate GARCH models.

[5] See Table A1 for a summary review of the recent literature on price volatility transmission between agricultural and crude oil markets.

[6] Notably the 2006 food crisis, the financial crash of 2008 and the enforcement of major biofuel policies such as the U.S. Energy Policy Act of August 2005 or the Energy Independence and Security Act of December 2007.

$$H_t = CC' + F'\varepsilon_{t-1}\varepsilon'_{t-1}F + G'H_{t-1}G \quad (2)$$

where conditional expectations and covariances are $\mu_t = \mathrm{E}_{t-1}[r_t]$ and $H_t = E_{t-1}[\varepsilon_t\varepsilon'_t]$, respectively.[7] Moreover, $\xi_t \sim N(0, I_K)$ is a K-dimensional innovation vector. Model parameters are collected in the matrices G, F and C, with the latter being lower triangular. With vech($\cdot$) denoting an operator that stacks the elements on and below the diagonal of a $K \times K$ matrix into a $K^* = K(K+1)/2 \times 1$ dimensional vector, the so-called half-vec model is

$$h_t = \omega + A\eta_{t-1} + Bh_{t-1} \quad (3)$$

where $h_t = \mathrm{vech}(H_t)$, $\eta_t = \mathrm{vech}(\varepsilon_t\varepsilon'_t)$, $\omega = \mathrm{vech}(CC')$, $A = D_K^+(F \otimes F)'D_K$ and $B = D_K^+(G \otimes G)'D_K$, with D_K and D_K^+ denoting the so-called duplication matrix and its generalized inverse, respectively.[8] The half-vec model allows for the definition of a Martingale difference

$$u_t = \eta_t - h_t \quad (4)$$

which can serve as a heteroskedastic ($E_{t-1}[u_t u'_t] = \Omega_t$) innovation process within a vector MA representation of $\eta_t = \mathrm{vech}(\varepsilon_t\varepsilon'_t)$, that is,

$$\eta_t = \omega + A\eta_{t-1} + B\left(\eta_{t-1} - u_{t-1}\right) + u_t \quad (5)$$

$$= \tilde{\omega} + \Theta(L)\, u_t \quad (6)$$

$$= \tilde{\omega} + \Theta(L)\,\Omega_t^{1/2}\Omega_t^{-1/2}u_t \quad (7)$$

$$= \tilde{\omega} + \Psi_t(L)\, v_t \quad (8)$$

where $\Theta(L) = (I - \mathcal{A}L)^{-1}(1 - BL)$, $\mathcal{A} = A + B$ and $\tilde{\omega} = (I - \mathcal{A})^{-1}\omega$. The invertibility of $(1 - \mathcal{A}L)$ holds under the assumption that the spectral radius of $\mathcal{A}$ is less than unity (Engle & Kroner, 1995). Noticing that the elements in u_t are contemporaneously correlated, the effects of orthogonalized shocks—denoted $v_t = \Omega_t^{-1/2}u_t$—are retrieved from the model in (8) as

$$\Psi_t(L) = \Theta(L)\,\Omega_t^{1/2} \quad (9)$$

Unlike in homoskedastic VARs,[9] the impulse responses implied by $\Psi_t(L)$ are time-varying and depend on unconditional fourth-order moments of the MGARCH innovations ξ_t, that is, E[vec($\xi_t\xi'_t$) $\otimes$ vec($\xi_t\xi'_t$)$'$]. Fengler and Herwartz (2018) employ the half-vec MA representation in (5) to determine iterative d-step ahead predictions of Ω_t at each time origin t, denoted $\Omega_{d,t}$. Joining these predictions with the estimated MGARCH polynomial $\Theta(L)$ obtains time-varying impulse response matrices $\Psi_{d,t}$. Subsequently, the proportion of the D-step ahead forecast error variance of variable i, accounted for by innovations in variable j is

$$\lambda_{ij,t}^{(D)} = \frac{\sum_{d=1}^{D}\left(\psi_{ij}^{(t,d)}\right)^2}{\sum_{d=1}^{D}\sum_{0j=1}^{K^*}\left(\psi_{ij}^{(t,d)}\right)^2}, \; d = 1, \ldots, D \quad (10)$$

where $\psi_{ij}^{(t,d)}$ is a typical element of the d-step ahead effect matrix $\Psi_{d,t}$. To fully assess the result in (10), it is important to notice that the "variables" in η_t (and hence u_t) refer to squared terms ($\varepsilon_{i,t}^2$, variances) and cross products ($\varepsilon_{it}\varepsilon_{jt}$, covariances). The elements within the ith (jth) row (column) of the matrices $\Psi_{d,t}$ quantify volatility reception (transmission) patterns among the variables η_i and η_j, $i \neq j$. Adopting the indices of Fengler and Herwartz (2018), we next define spot measures of spillover dynamics, which provide insights into food–oil (co)variance linkages.

3.2 | Aggregate and directional spillovers

Figure 1 displays a schematic disaggregation of the effect matrices $\Psi_{d,t}$ for the case of the ethanol group. By convention, the log price change of oil is the first element of r_t. The agricultural markets are ordered second (corn), third (wheat) and fourth (sugar) within the analyzed vector of log price changes.

The "Total Spillover Index" essentially provides information about the joint interdependence among all K^* variables η_i up to horizon D. From the statistics defined in (10), it obtains as an aggregation (column- or row-wise) of the individual (co)variance effects displayed in Figure 1, that is,[10]

$$S_t = \frac{\sum_{i,j=1,\, i\neq j}^{K^*}\lambda_{ij,t}}{K^*} \quad (11)$$

Moreover, statistics in each column (row) of $\Psi_{d,t}$ correspond to directional effects originating in (going to) specific variables in η_t. Directional spillovers—that is, volatility transmissions and receptions—read as

$$T_{j,t} = \frac{\sum_{i=1,\, i\neq j}^{K^*}\lambda_{ij,t}}{K^*} \quad \text{and} \quad R_{i,t} = \frac{\sum_{j=1,\, j\neq i}^{K^*}\lambda_{ij,t}}{K^*} \quad (12)$$

respectively. For instance, as displayed in Figure 1, row 5 of $\Psi_{d,t}$ contains effects received by the variance of corn (η_{5t})

[7] The matrix square root of H_t obtains as $H_t^{1/2} = \Gamma_t\Xi_t^{1/2}\Gamma'_t$, where the eigenvectors of H_t are the columns of Γ_t, and the diagonal matrix Ξ_t has the eigenvalues of H_t along its diagonal.

[8] With reference to a symmetric square $K \times K$ matrix Z, the $K^2 \times K$ duplication matrix D_K is defined by the property vec(Z) = $D_K$vech(Z).

[9] See Lütkepohl (2007), Chapter 2.

[10] Focusing on cross-market dynamics, "diagonal" statistics $\lambda_{ii,t}^{(D)}$ do not contribute to (co)variance spillovers. For notational convenience, the underlying forecast horizons, d, D are omitted from the definition of spillover indices.

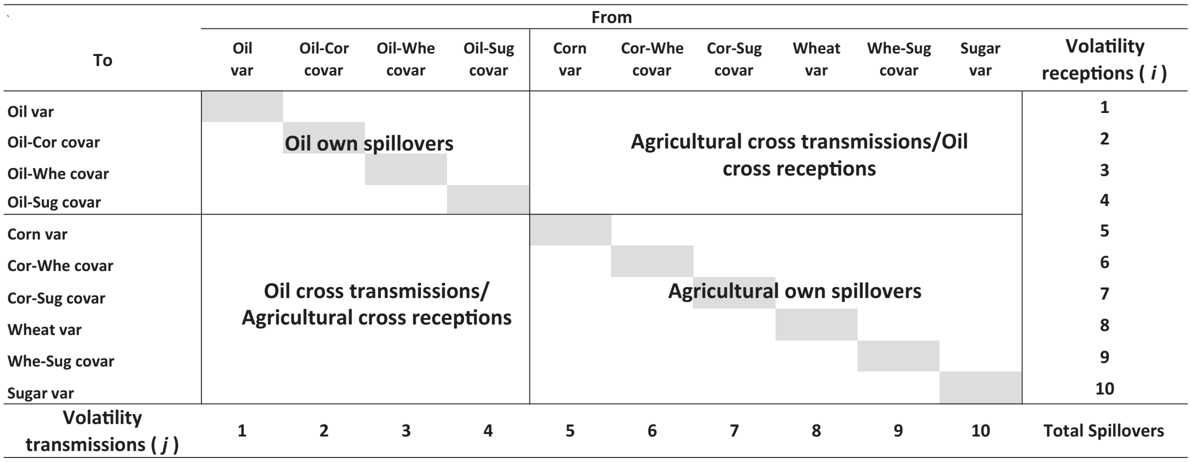

FIGURE 1 Structure of a typical effect matrix $\boldsymbol{\Psi}_{d,t}$ in the case of the ethanol group

Note: This table illustrates (co)variation patterns in terms of volatility transmissions from variables η_j (columns) and volatility receptions of variables η_i (rows). Separated by division lines, four additional segments represent sector-specific transmissions and receptions on crude oil and agricultural markets.

from the six covariances (η_{jt}, $j = 2,3,4,6,7,9$), and the variances of crude oil, wheat, and sugar (η_{jt}, $j = 1,8,10$). Similarly, column 5 of $\Psi_{d,t}$ collects the effects transmitted by corn's variance to the remaining (co)variances. Accordingly, net spillovers are

$$N_{i,t} = T_{i,t} - R_{i,t} \tag{13}$$

If $N_{i,t}$ is positive, the variable η_i acts as a net volatility transmitter in time t. A negative outcome quantifies a net reception. By construction, $\sum_{i=1}^{K^*} N_{i,t} = 0$ for all t.

3.3 | Volatility spillovers among food and oil markets

At finer levels of aggregation, the following sectoral statistics capture effects among products sharing common characteristics or dynamics, such as feedstock markets.

1. The index of "*Oil cross transmissions/Agricultural cross receptions*" gathers volatility spilling from crude oil (co)variations to agricultural markets

$$T_t^{(O)} = R_t^{(A)} = \frac{\sum_{i=1}^{4} \sum_{j=5}^{K^*} \lambda_{ij,t}}{K^*} \tag{14}$$

2. The "*Oil own spillovers*" index summarizes volatility originating and spilling over to (co)variations of crude oil

$$S_t^{(O)} = \frac{\sum_{i,j=1,\, i\neq j}^{4} \lambda_{ij,t}}{K^*} \tag{15}$$

3. In analogy to $T_t^{(O)}$ and $R_t^{(A)}$, "*Agricultural cross transmissions/crude oil cross receptions*" gather volatility spilling from agricultural (co)variations to crude oil markets

$$T_t^{(A)} = R_t^{(O)} = \frac{\sum_{i=5}^{K^*} \sum_{j=1}^{4} \lambda_{ij,t}}{K^*} \tag{16}$$

4. Similarly to $S_t^{(O)}$, "*Agricultural own spillovers*" summarize volatility originating and spilling over to (co)variations of agricultural markets

$$S_t^{(A)} = \frac{\sum_{i,j=5,\, i\neq j}^{K^*} \lambda_{ij,t}}{K^*} \tag{17}$$

In addition, the relative contribution of crude oil to uncertainty at agricultural markets obtains as the share

$$Sh_t^{(A)} = R_t^{(A)} / \left(R_t^{(A)} + S_t^{(A)} \right) \tag{18}$$

3.4 | Market-specific volatility receptions

Owing to commodity-specific characteristics (e.g., market size and liquidity, internationally traded volumes, relevance as staple food or industrial raw material), oil price uncertainties might threaten the stability of specific agricultural markets in different manners and with varying strength. Measures of market-specific exposures to crude oil shocks at higher frequencies allow on-time monitoring of potentially emergent food security threats and likely facilitate focalized interventions such as safety nets, import promotions or strategic stock releases to stabilize prices.

Let $a_m = \{a_1, a_2, a_3\}$ denote a set of indices of vectors η_t referring to feedstock (co)variations that involve a particular market "m," $m \in \{corn, wheat, sugar, soybean, rapeseed, palm\}$. For instance, in the case of the ethanol group, we have $m \in \{corn, wheat, sugar\}$. Noticing that log price changes of wheat are ordered after those of crude oil and corn, for example, $a_{wheat} = \{6, 8, 9\}$ (see $\Psi_{d,t}$ in Figure 1). At the level of single food markets, total volatility receptions and those originating in crude oil markets read, respectively, as

$$R_t^{(m)} = \frac{\sum_{i \in a_m} \sum_{j=1, j \neq i}^{K^*} \lambda_{ij,t}}{K^*} \quad \text{and} \quad RfO_t^{(m)} = \frac{\sum_{i \in a_m} \sum_{j=1}^{4} \lambda_{ij,t}}{K^*} \tag{19}$$

3.5 | Biofuel policies and volatility receptions from crude oil markets

The empirical evidence on the impact of crude oil volatility on agricultural commodities is heterogeneous. While some authors confirm recently strengthened linkages among crude oil, biofuels, and distinct agricultural markets (e.g., Serra et al., 2011; Wu & Li, 2013), others find no (or minor) evidence of crude oil volatility influencing agricultural commodities (e.g., Gardebroek & Hernandez, 2013; Kaltalioglu & Soytas, 2011; Qiu, Colson, Escalante, & Wetzstein, 2012; Zhang, Lohr, Escalante, & Wetzstein, 2009). Zilberman, Hochman, Rajagopal, Sexton, and Timilsina (2012) argue that tracing the directional effects of changes in biofuel prices necessitates a thorough understanding of the causes of agricultural price changes. Accordingly, a stream of recent literature (e.g., Bobenrieth, Wright, & Zeng, 2013; Mitchell, 2008; Wright, 2011) suggests that the main distinction between the 2006 food crisis and previous turmoil episodes in grain and oilseed markets is the emergence of biofuels and enactments of ambitious policies designed for their support. In this regard, Abbott (2013), Carter, Rausser, and Smith (2012) and Tyner (2010) motivate the consideration of policy interventions at precise time points to reveal changes in the food–oil link. Therefore, our empirical analysis of cross-market origins of food price variations complements broad unconditional assessments with evidence from regression models that are informative on the role of crude oil volatility, general financial market uncertainty and precisely defined policy regimes.

4 | VOLATILITY SPILLOVERS IN FOOD–OIL DYNAMIC SYSTEMS

In this section, we introduce the analyzed vector systems of daily log price changes and provide some unconditional descriptive statistics, as well as BEKK model estimates to quantify conditional (co)variances. Turning to model implications, we discuss specific market relations in terms of overall and directional volatility spillovers and highlight the specific role of crude oil markets in contributing to uncertainties on agricultural markets. Finally, we use market-specific volatility receptions to uncover the effects of biofuel policies on feedstock price uncertainties.

4.1 | Log price changes on food and crude oil markets

Covering the period between October 3, 1995, and February 27, 2015, we analyze daily data for spot prices of corn, wheat, sugar, soybean, palm and crude oil, as well as one futures series for rapeseed. Time series have been drawn from Thomson Reuters.

Table 1 documents means and standard deviations of log price changes for distinguished subperiods. During Period I, most agricultural commodities faced declining prices until 2000, which revert thereafter, characterizing the beginning of the so-called "super cycle" (Erten & Ocampo, 2013). Average price changes turn positive in Period II. Due to price drops in late-2008 and 2014, average log crude oil price changes are negative in Period II. Moreover, unconditional standard deviations for wheat, corn, and soybean increased by 64%, 34%, and 11%, respectively, suggesting that these markets might have experienced strengthened expositions to risk receptions.

4.2 | BEKK model evaluations

With reference to the vector return specification in (1), we regress vector-valued log price changes r_t on lagged values r_{t-1}, an intercept and a time dummy variable indicating Period II with unit values.[11] Subsequent to the linear regressions, we subject estimated residual vectors $\hat{\varepsilon}_t$ to QML estimation of the covariance dynamics in (2).Table A2 provides model estimates for the two commodity groups. For the ethanol system, t-ratios point to a few marginally significant off-diagonal elements of the news response parameters in the matrix F. In the case of the biodiesel group, the likelihood ratio for testing the null hypothesis of a so-called diagonal BEKK model is highly significant, with a corresponding p-value below 0.1% (test statistic of 72.12; χ^2-distributed with 24 degrees of freedom under the null hypothesis of diagonal matrices F and G). Hence, the empirical data support the formalization of a rich cross-variable dynamic (co)variance structure that is specific to the BEKK model.

[11] Consistent lag order selection for r_t is quite demanding in case of VAR residuals that exhibit MGARCH covariance profiles. For market efficiency considerations, we opt for short-order models (i.e., VAR(0) or VAR(1)). Conditioning the QML MGARCH estimation on VAR(1) or VAR(2), residuals obtains quantitatively almost-identical covariance paths. For the ethanol commodity group, almost-identical MGARCH covariance estimates are also obtained from modeling centered returns, that is, VAR(0) residuals. Similarly, MGARCH outcomes are almost invariant to alternatively assuming a common mean or a shift in mean returns to occur with the food/financial crisis (Period I vs. Period II).

TABLE 1 Descriptive statistics of log price changes

Log price changes	Mean Period I	Mean Period II	*SD* Period I	*SD* Period II	Δ%
Oil, crude WTI Cushing US$/BBL	0.464	−0.085	24.74	23.31	−6%
Corn, No. 2 yellow US$ Cts/Bu	−0.146	0.255	15.97	21.36	34%
Wheat, No. 2 hard (Kansas) US$ Cts/Bu	−0.035	0.043	15.31	25.07	64%
Sugar, raw (ISA) daily price US$ Cts/lb	0.068	0.009	21.80	20.44	−6%
Soybean oil, crude Decatur US$ Cts/lb	−0.087	0.180	14.57	16.12	11%
Rapeseed oil, Dutch FOB NWE 1 m fwd EUR/MT	0.134	0.042	19.14	14.43	−25%
Palm oil, crude MAL CIF Rdam US$/MT	−0.140	0.205	18.61	17.92	−4%

Note: Means and standard deviations (*SD*s) have to be divided by 1,000. The results for Period I (Period II) correspond to the subsamples October 1995 until December 2005 (January 2006 until February 2015). The column labeled Δ% documents percentage changes from Period I to Period II.

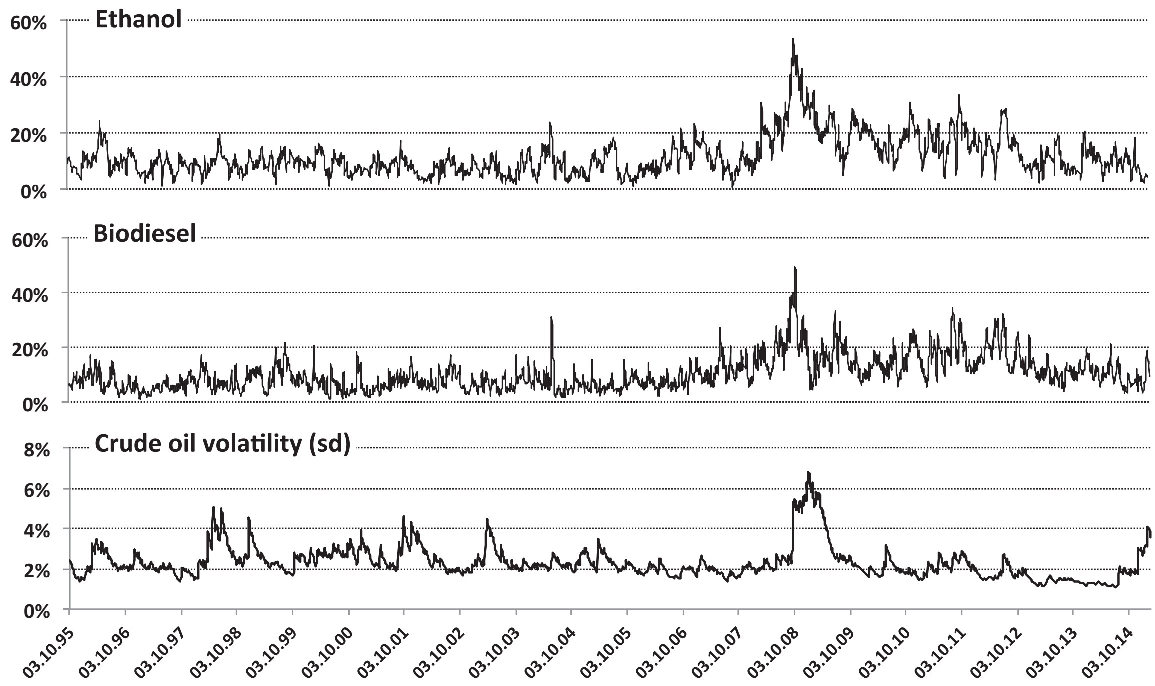

FIGURE 2 Total volatility spillovers and crude oil price volatility

Notes: The upper and medium panels display total spillovers S_t as defined in (11) for each commodity group and implied by the QML estimates of the model in (1) and (2). The bottom panel displays conditional standard deviations of crude oil log price changes as implied by an univariate GARCH (1,1) model. The displayed conditional oil volatilities are very similar to alternative estimates from the BEKK models and show unconditional correlations of 0.998 and 0.963 for the ethanol and biodiesel group, respectively.

4.3 | Aggregate and directional spillovers

As depicted in Figure 2, for both commodity groups total volatility spillovers exhibit an upturn during Period II, especially in the aftermath of the financial breakdown in September 2008 and during the first half of 2011, when most of the considered agricultural markets attain maximum prices.[12] While average total spillovers almost doubled in Period II, conditional standard deviations of crude oil slightly decreased on average by 12%. However, unconditional correlations between crude oil standard deviations and total spillover indices markedly shift upward (i.e., from 0.18 (0.03) for the ethanol (biodiesel) group in Period I to 0.61 (0.32) in Period II).[13] The lower crude oil volatility coupled with a strengthened link with feedstock markets during Period II signals a change in the relevant volatility transmission channels, which almost coincides with enactments of key biofuel policies.

[12] Corn reaches a maximum price later in August 2012.

[13] The spillover indices displayed in Figure 2 are similar in shape to those in Trujillo-Barrera, Mallory, and Garcia (2012). However, methodologically it is worth noting that—unlike S_t defined in (11)—their spillover indices depend by construction on crude oil volatility.

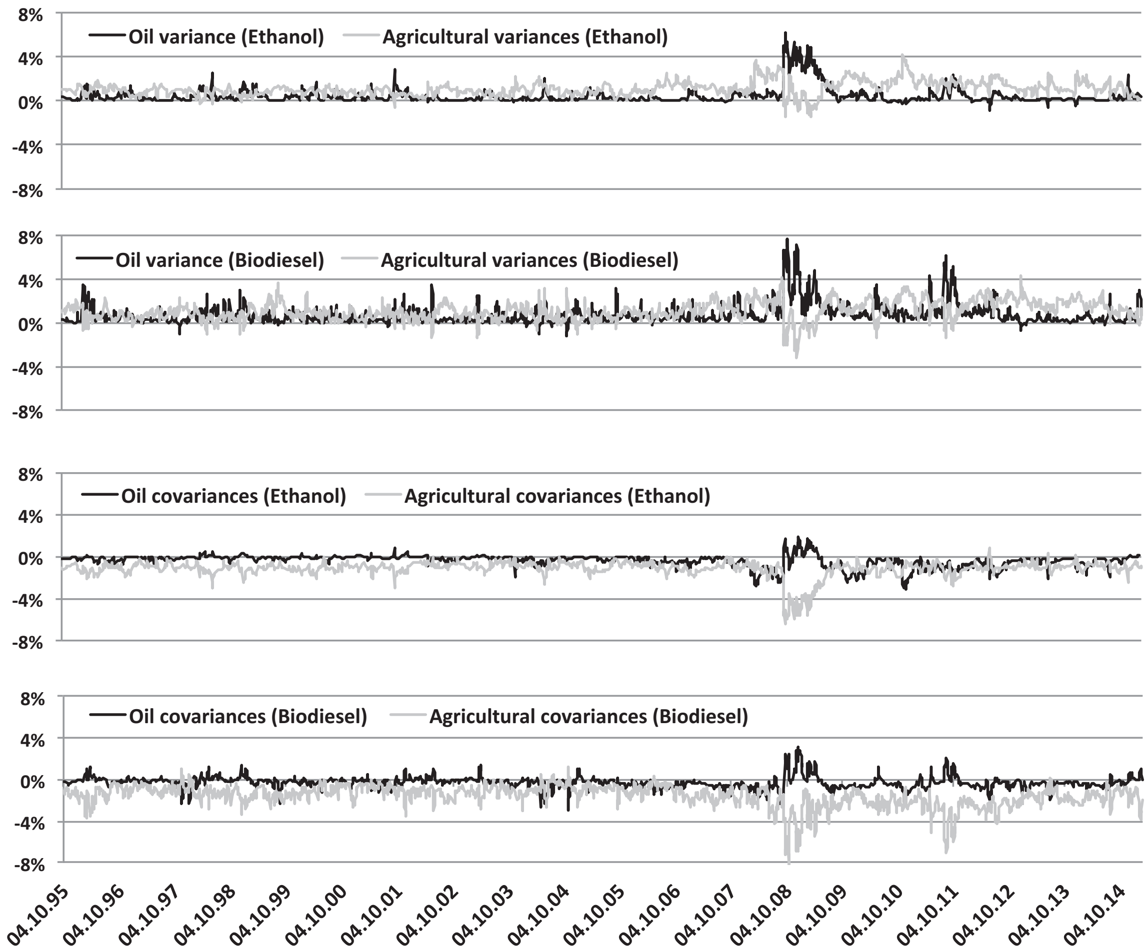

FIGURE 3 Net directional volatility spillovers

Note: The graphs display sums of net volatility transmissions as defined in (13), separated by commodity types (crude oil and agricultural). Positive values represent net volatility transmissions, while negative ones denote net receptions.

Figure 3 displays net spillovers of variances and covariances distinguishing crude oil and agricultural commodities. Crude oil and agricultural variances have mainly acted as net volatility transmitters, whereas particularly agricultural covariances have been receiving volatility. The volatility receptions of biodiesel covariations are larger than those for ethanol, suggesting that vegetable oil markets might be more sensitive to shocks originating in either agricultural or crude oil markets, in particular during Period II. Liquidity differences might plausibly explain the distinctive behavior of ethanol and biodiesel feedstock markets. Additionally, the industrial use of the considered vegetable oils—which includes their use as biodiesel feedstocks—grew much faster during Period II compared with the industrial use of grains or sugar.[14]

4.4 | Sectoral spillovers

As documented in Table 2, the largest contributions to aggregated spillovers can be characterized as effects originating from and spilling to agricultural markets ($S_t^{(A)}$). In order to assess inter-sectoral vulnerabilities, $R_t^{(A)}$ ($T_t^{(O)}$) collects effects of shocks originating in crude oil and spilling over to agricultural markets. On average, this index is larger for biodiesel compared with ethanol feedstocks during both subperiods. Hence, vegetable oils are more exposed to crude oil developments compared with grains and sugar. Moreover, agricultural and crude oil markets experienced a tightening, which can be seen from two comparative assessments of average sectoral statistics. First, in terms of $R_t^{(A)}$, average outcomes have more than doubled for Period II compared with Period I. Second, the interaction indices of crude oil-feedstock covariations ($S_t^{(O)}$) are on average almost twice as

[14] Own estimates based on information from the USDA Foreign Agricultural Service (retrieved from https://apps.fas.usda.gov/psdonline/app/index.html#/app/advQuery). While the industrial use of corn—the largest processed ethanol feedstock—grew by 79%, the use of soybean, rapeseed and palm grew by factors of six, four, and three, respectively.

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TABLE 2 Average sectoral spillovers

Ethanol	S	$R^{(A)}$	$S^{(O)}$	$S^{(A)}$	$T^{(A)}$	$Sh^{(A)}$
Period I	86.78	6.42	18.66	56.74	4.95	0.10
Period II	151.73	16.28	34.41	84.63	16.41	0.16
Δ%	75%	154%	84%	49%	231%	59%
Biodiesel						
Period I	72.82	9.54	16.69	39.51	7.09	0.19
Period II	140.82	18.98	31.18	74.31	16.36	0.20
Δ%	93%	99%	87%	88%	131%	5%

Note: Values (except for Δ% and $Sh^{(A)}$) have to be divided by 1,000. As defined in (14) and (16), $T_t^{(O)} = R_t^{(A)}$ and $T_t^{(A)} = R_T^{(O)}$, respectively. In addition, $Sh_t^{(A)}$ defined in (18) is an estimate of the relative contribution of crude oil to uncertainty on agricultural markets. See Table 1 for further details and Figure 1 for an illustrative display of the informational content of the sectoral indices.

TABLE 3 Volatility receptions from crude oil on feedstock markets

	Ethanol			Biodiesel		
$R^{(m)}$	Corn	Wheat	Sugar	Soybean	Rapeseed	Palm
Period I	43.86	42.35	19.05	28.05	27.26	26.57
Period II	66.83	62.36	37.30	56.40	51.49	47.69
Δ%	52%	47%	96%	101%	89%	79%
Mandate	71.04	67.33	39.21	58.71	57.42	50.07
Tax credit	65.84	59.69	37.56	59.46	49.39	49.58
Δ%	−7%	−11%	−4%	1%	−14%	−1%
$RfO^{(m)}$						
Period I	3.56	3.38	3.15	4.27	5.58	4.95
Period II	9.19	8.19	8.24	12.92	8.36	8.42
Δ%	158%	142%	162%	202%	50%	70%
Mandate	10.24	9.73	9.34	12.93	8.94	8.87
Tax credit	8.93	7.07	7.62	13.59	8.20	8.55
Δ%	−13%	−27%	−18%	5%	−8%	−4%

Note: The table documents reception statistics defined in (19). Average outcomes are provided by subperiods and conditioning on policy regimes prevailing in Period II. Reported statistics (except for Δ%) have been multiplied by 1,000. Mandate binding periods comprise September 2006 to March 2007, December 2008 to April 2010, and May 2011 to March 2014. Tax credit episodes include April 2007 to November 2008, May 2010 to April 2011, and April 2014 to February 2015.

large in Period II compared with Period I. From average shares $Sh^{(A)}$, one might conclude that uncertainties stemming from shocks to crude oil markets account for about one-fifth of the total volatility spillover receptions in feedstock markets during Period II (i.e., 0.16 (0.20) within the ethanol (biodiesel) group). Although the share of crude oil's uncertainty is larger for biodiesel, the contribution of oil markets to uncertainties on agricultural markets has grown more strongly for ethanol feedstocks in Period II (59%).

Apart from cross-sectoral developments from crude oil to agricultural markets, it is also interesting to see the reverse effects of shocks originating in agricultural and spilling over to crude oil markets. Although the average quotes of $T_t^{(A)}$ ($R_t^{(O)}$) are smallest among the four sectoral indices for Period I and both commodity groups, it approaches $R_t^{(A)}$ in Period II. For both commodity groups, it shows the largest growth among the four sectoral indices. With a focus on corn, wheat, and soybean, similar reverse spillovers have been reported by Nazlioglu et al. (2013) and Grosche and Heckelei (2016). To explain this outcome, Baumeister and Kilian (2014) and Nazlioglu et al. (2013) argue that developed countries' support of biofuels has strengthened information flows among energy and food markets. Nazlioglu et al. (2013) highlight two additional reasons to expect feedback spillover effects: first, traders in different markets might react jointly to noneconomic factors; and second, for portfolio strategies investors concentrate on price dynamics of key food crops such as wheat.

4.5 | Assessing the role of major biofuel policies

Observing an overall enhanced vulnerability of feedstock markets, the following refined analysis has two main purposes. First, it intends to unravel how the market-specific volatility receptions $RfO_t^{(m)}$ in (20) respond to price uncertainties on crude oil markets. Second, focusing on important channels of information flows, we test for changes in $RfO_t^{(m)}$ during distinct biofuel policy regimes that prevailed in Period II (de Gorter & Drabik, 2016).

4.5.1 | Feedstock volatility receptions

The results documented in Table 3 show that strengthened market integration emerges in terms of increased total volatility receptions on all feedstock markets. During the postcrisis timeframe (Period II), average volatility receptions are between 47% (wheat) and 101% (soybean) larger compared with average outcomes for the precrisis observations (Period I). While total receptions do not provide evidence regarding the origin of information flows, it is striking that the food crisis and the subsequent financial bust have intensified volatility receptions from crude oil markets ($RfO_t^{(m)}$). In absolute and relative terms, changes of volatility receptions point to sizable market heterogeneities. In relative terms, soybean suffered a threefold upsurge of volatility receptions. While average statistics for $RfO^{(corn)}$, $RfO^{(wheat)}$ and $RfO^{(sugar)}$ also markedly augmented by a factor of about 2.5, corresponding statistics $RfO^{(rapeseed)}$ and $RfO^{(palm)}$ increased by 50% and 70%, respectively. Focusing on volatility receptions on corn markets, our analysis allows for an interesting comparison with the results of Trujillo-Barrera et al. (2012). According to our estimates, the relative contribution of crude oil to volatility receptions on corn markets (i.e., $RfO^{(corn)}/R^{(corn)}$) is 13.8% in Period II. For the period from 2006 to 2011, Trujillo-Barrera et al. (2012) document a similar relative contribution of 14% under the assumption of exogenous crude oil market dynamics and volatilities. The remaining feedstock vulnerabilities to shocks originating in crude oil markets are between 13.1% ($RfO^{(wheat)}/R^{(wheat)}$) and 22.9% ($RfO^{(soybean)}/R^{(soybean)}$) during Period II. Pointing to generally enhanced food–oil linkages, it is worth noting that in precrisis timeframes (Period I) feedstock vulnerabilities $RfO^{(m)}/R^{(m)}$ were 8% for corn and wheat, and about 16% for sugar and soybean.[15] In addition to the augmented relative contributions of crude oil to uncertainties on different agricultural markets in Period II, differentiated effects between policy regimes also warrant consideration. Seemingly at odds with the arguments of de Gorter et al. (2015), (binding) mandate implementations appear to be characterized by enhanced crude oil spillovers to agricultural markets (aside from the case of soybean). In order to further analyze the role of biofuel policies in shaping food–oil linkages, two remarks are worth mentioning. On the one hand, it is likely that both market heterogeneities and crude oil volatility are jointly important to unravel marginal effects that can be traced back to enactments of distinct biofuel policies. On the other hand, the detection of such marginal effects is complicated by the fact that all policy enactments took place within the postcrisis timeframe (Period II). Hence, general financial market uncertainty might have also confounded information flows between crude oil and feedstock markets.

4.5.2 | Feedstock volatility receptions and the role of biofuel policies

Policy enactments and descriptive evidence

Within our sample period, biofuel policies were enacted during Period II from September 2006 until February 2015, covering a total of 2,216 observations (see also the notes to Table 3). These policy periods capture three episodes of binding mandates, to which we refer as Man I to Man III, as well as three episodes of binding tax credits, labeled as Tax I to Tax III. Specifically, Man I, Man II and Man III (Tax I, Tax II, and Tax III) cover the periods September 2006 to March 2007, December 2008 to April 2010, and May 2011 to March 2014 (April 2007 to November 2008, May 2010 to April 2011, and April 2014 to February 2015).[16] Overall, binding mandate and tax credit policies were active for 1,282 and 934 sample observations, respectively.

[15] The two remaining biodiesel feedstock markets—rapeseed and palm—experienced higher vulnerabilities to crude oil shocks during the precrisis period of 20.5% and 18.6%, respectively.

[16] Although not explicitly stated in de Gorter and Drabik (2016), we assume two additional periods of binding policies after April 2011, that is, Man III and Tax III. As identified by de Gorter, Drabik, and Just (2015, p. 155), a U.S. tax credit was enacted in April 2014 and extended through 2015. Nonetheless, an enactment does not necessarily imply that a policy is binding, that is, determining biofuel prices.

Figure 4 contrasts crude oil volatility receptions of feedstock markets (i.e., $RfO_t^{(corn)}$, first row of Figure 4; average receptions $RfO_t^{(m)}$, $m \neq corn$, second row) against crude oil standard deviations (third row). During Tax I and Man II, enhanced volatility receptions on feedstock markets coincide with extended levels of crude oil volatility. In its bottom panel, Figure 4 also displays the (implied) Volatility Index of the Chicago Board Options Exchange (VIX) to capture patterns of general financial market uncertainties.[17] The evolution of the VIX highlights the important role of general financial market turmoil in shaping uncertainty receptions on agricultural markets. For instance, despite relative tranquil crude oil markets, volatility receptions of feedstock markets sharply increase with the "Black Monday" stock market crash of August 8, 2011. Further critical episodes of general uncertainties developed subsequent to the declaration of default of Lehman Brother's on September 15, 2008, and the so-called "Flash Crash" of May 6, 2010.

Evidence from profile regressions

Allowing for a flexible conditioning of volatility reception patterns on feedstock markets, we consider regression models of the following type

$$RfO_t^{(m)} = \gamma_1^{(m)} + D_t^{(cri)}\gamma_2^{(m)} + Tax_t\,\beta_1^{(m)} + Man_t\,\beta_2^{(m)} + sdoil_t\,\gamma_3^{(m)} + sdoil_t\cdot D_t^{(08)}\,\gamma_4^{(m)} + sdoil_t \cdot D_t^{(10)}\,\gamma_5^{(m)} + sdoil_t\cdot D_t^{(11)}\,\gamma_6^{(m)} + e_t \quad (20)$$

By model specification, intercept terms $\gamma_1^{(m)}$ provide a quantitative assessment of unconditional volatility receptions in Period I, during which no biofuel policy was enacted. The dummy variable $D_t^{(cri)}$ indicates additional effects on volatility transmission that occurred in Period II without correspondence with biofuel policies. Moreover, the regression includes (a) effects of crude oil volatility ($\gamma_3^{(m)}$) and (b) effects of this variable that are specific to particular episodes of general financial unrest ($\gamma_i^{(m)}$, $i = 4, 5, 6$). In taking account of general financial uncertainty, dummy variables $D_t^{(08)}$, $D_t^{(10)}$ and $D_t^{(11)}$ capture VIX levels above 0.03 subsequent to the three disruptive events mentioned above ("Black Monday," Lehman default, "Flash crash"). After these events, the VIX took some time to return to more regular levels below 0.03 (see also the fourth row of Figure 4). The three periods of enhanced financial turmoil cover 217 ($D_t^{(08)}$, September 2008 to June 2009), 43 ($D_t^{(10)}$, May 2010 to June 2010) and 88

[17] The VIX is a 30-day forward-looking measure of investors' risk perceptions. VIX data were obtained from the Federal Reserve Bank of St. Louis (retrieved from https://fred.stlouisfed.org/). A few missing observations have been replaced by linear interpolation.

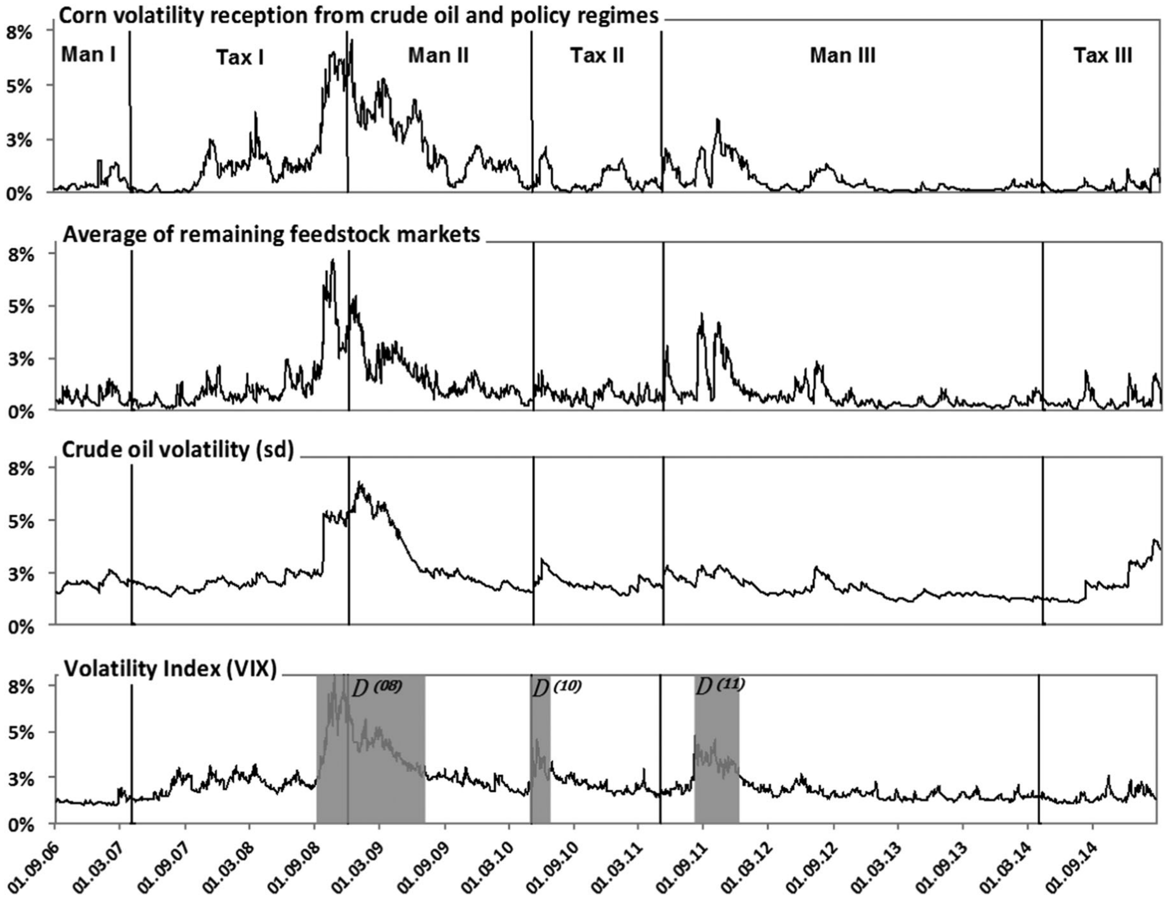

FIGURE 4 Volatility receptions from crude oil and binding policy periods
Note: The upper graph depicts corn volatility receptions from crude oil ($RfO_t^{(\text{corn})}$, see (19)) over successive periods between September 2006 and February 2015 (Period II) when either a mandate (Man I, II, III) or a tax credit policy (Tax I, II, III) was binding. Mandate periods comprise September 2006 to March 2007, December 2008 to April 2010, and May 2011 to March 2014. Tax credits were enforced during April 2007 to November 2008, May 2010 to April 2011, and April 2014 to February 2015. The second panel shows average volatility receptions for the remaining feedstock markets. The third and fourth graphs show crude oil volatility and the VIX Volatility Index (divided by 1,000), respectively. Subsequent to singular events (Lehman default, "Flash Crash", "Black Monday"), shaded areas of the VIX panel cover high-uncertainty episodes in financial markets during September 2008 to June 2009 (D^{08}), May 2010 to June 2010 (D^{10}), and August 2011 to November 2011 (D^{11}).

($D_t^{(11)}$, August 2011 to November 2011) observations.[18] In order to isolate the marginal effects of enactments of distinct categories of biofuel policies, the profile regression in (20) includes two binary indicators of biofuel policies, namely, Tax_t and Man_t, which refer to tax credit (Tax I to Tax III) and mandate (Man I to Man III) periods, respectively. Finally, e_t is an uninformative model residual. Complementing market-specific results, $m = 1, 2, \ldots, 6$, we provide an overall assessment by imposing parametric restrictions of the form $\gamma_i^{(m)} = \gamma_i$, $i = 1, 2, \ldots, 6$, and $\beta_i^{(m)} = \beta_i$, $i = 1, 2$.[19] If the arguments of de Gorter et al. (2015) carry over to (co)variance dynamics of the food–oil nexus, one would expect $\beta_1^{(m)} > \beta_2^{(m)}$.

Table 4 summarizes parametric estimates from the profile regressions given in (20). Coefficient estimates $\hat{\gamma}_1^{(m)}$ deliver significant yet negative values for each feedstock, signaling lower uncertainty flows originating in crude oil markets during no-policy periods. During the crisis period, all agricultural markets experienced additional positive and significant spillover receptions from crude oil ($\hat{\gamma}_2^{(m)}$). Moreover, the magnitudes of parameter estimates $\hat{\gamma}_3^{(m)}$ highlight the active role of crude oil volatility for uncertainty receptions in each agricultural market. Accounting for crude oil and financial market

[18] The employed threshold value of 0.03 is quite close to the 86% quantile of the VIX. In only 10% of all observations is the displayed VIX beyond 0.033. We believe that defining the periods in this way does not bias detecting marginal transmission patterns that can be traced back to policy categories. The first period covers observations that belong to both policy categories (Tax I, Man II), while the second and third periods are fully covered by time frames when tax credits (Tax II) and mandates (Man III) were in place, respectively.

[19] Even if the imposed restrictions are not met by the data, restricted estimates hold interest since pooling heterogeneous parameters is effective to reduce estimation uncertainty.

TABLE 4 Profile regression results (see (20)) for feedstock volatility receptions

	Ethanol			Biodiesel			Feedstocks
	Corn	Wheat	Sugar	Soybean	Rapeseed	Palm	jointly
$\hat{\gamma}_1$ *no policy*	−4.34	−2.97	−5.08	−3.98	−3.24	−2.84	−3.74
	(−13.53)	(−10.02)	(−13.04)	(−9.26)	(−8.01)	(−7.15)	(−23.09)
$\hat{\gamma}_2$ *crisis*	0.76	0.46	1.86	6.55	1.10	1.01	1.96
	(5.46)	(3.09)	(9.61)	(19.45)	(4.92)	(4.68)	(17.16)
$\hat{\gamma}_3$ *sdoil*	3.24	2.60	3.37	3.38	3.62	3.19	3.23
	(23.09)	(20.11)	(19.19)	(18.98)	(19.76)	(18.39)	(45.84)
$\hat{\gamma}_4$ $(sdoil \cdot D^{(08)})$	5.28	4.73	4.55	4.44	1.22	0.78	3.50
	(27.63)	(22.64)	(24.31)	(12.42)	(4.58)	(3.00)	(30.27)
$\hat{\gamma}_5$ $(sdoil \cdot D^{(10)})$	1.05	−0.15	−0.97	1.15	0.89	1.38	0.56
	(3.69)	(−0.93)	(−9.22)	(3.02)	(2.92)	(2.74)	(3.39)
$\hat{\gamma}_6$ $(sdoil \cdot D^{(11)})$	3.98	5.81	4.18	6.41	8.81	6.78	5.99
	(13.11)	(15.41)	(15.10)	(12.67)	(13.33)	(11.41)	(27.98)
$\hat{\beta}_1$ *Tax*	3.74	2.49	2.24	2.20	2.09	3.13	2.65
	(15.72)	(11.46)	(8.97)	(4.96)	(7.37)	(10.39)	(18.33)
$\hat{\beta}_2$ *Man*	3.19	2.99	2.02	−0.53	1.08	2.21	1.83
	(16.22)	(14.17)	(9.39)	(−1.33)	(4.30)	(7.57)	(13.75)
$(\hat{\beta}_1 - \hat{\beta}_2)$ (*Tax - Man*)	0.55	−0.50	0.22	2.74	1.01	0.92	0.82
	(2.00)	(−1.85)	(0.99)	(6.02)	(3.36)	(2.49)	(5.76)
RfO_{Tax}	7.15	5.61	6.30	12.08	7.76	8.19	7.85
RfO_{Man}	6.60	6.11	6.08	9.34	6.76	7.27	7.03
Δ%	8%	−8%	4%	29%	15%	13%	12%

Note: To improve the scale properties of the estimates, the dependent variables $RfO_t^{(m)}$ defined in (19) have been multiplied by 1,000 (*t*-ratios in parentheses). The noncrisis (crisis) episode includes October 1995–December 2005 (January 2006 to February 2015). The "*Tax - Man*" panel documents a statistic for testing the null hypothesis of equal effects under both biofuel policy categories ($H_0: \hat{\beta}_1 = \hat{\beta}_2$). The bottom lines show model-implied average uncertainty receptions for both policy periods (see (21) and (22)) and the corresponding change in percentage points. For further notes, see Figure 4.

uncertainty jointly, $\hat{\gamma}_4^{(m)}$ to $\hat{\gamma}_6^{(m)}$ show particularly large interaction effects subsequent to the "Black Monday" crash of August 2011, followed in magnitude by the financial bust of September 2008. While tax credit impacts seem more homogeneous across markets ($\hat{\beta}_1^{(m)}$), during mandate enforcements ($\hat{\beta}_2^{(m)}$) crude oil spills over (on average) to ethanol feedstocks with more strength, in particular for corn. Providing conforming evidence for the theoretical arguments of de Gorter et al. (2015), significance tests for the difference between estimates $\hat{\beta}_1^{(m)}$ and $\hat{\beta}_2^{(m)}$ reveal that spillover receptions of agricultural markets are larger during tax credit enactments. This result holds for individual markets (except for wheat) and the joint model. Proceeding beyond the comparison of parameter estimates, the profile regressions in (20) allow determining policy-specific average reception levels as

$$RfO_{Tax}^{(m)} = \hat{\gamma}_1^{(m)} + \hat{\gamma}_2^{(m)} + \hat{\beta}_1^{(m)} + E[sdoil_t]\,\hat{\gamma}_3^{(m)} \tag{21}$$

and

$$RfO_{Man}^{(m)} = \hat{\gamma}_1^{(m)} + \hat{\gamma}_2^{(m)} + \hat{\beta}_2^{(m)} + E[sdoil_t]\,\hat{\gamma}_3^{(m)} \tag{22}$$

Approximating $E[sdoil_t]$ by the average level of crude oil volatility during policy periods of 2.16%,[20] the bottom panel of Table 4 shows average reception levels for both policy periods, leaving out the marginal effects assigned to the identified episodes of general market uncertainties ($D_t^{(08)}$, $D_t^{(10)}$, and $D_t^{(11)}$). For instance, as implied by the estimates in the rightmost column of Table 4, the pooling of all feedstocks obtains approximations RfO_{Tax} and RfO_{Man} of 7.85 and 7.03, respectively. Hence, on average volatility receptions are about 12% larger during the enactment of tax credits. Moreover, during tax implementations, spillover effects are stronger for biodiesel compared with ethanol feedstocks. Crude oil uncertainty receptions in soybean markets increase the strongest (i.e., by 29%), followed by rapeseed (15%) and palm (13%), whereas the impacts on corn (8%) and sugar (4%) are comparatively weaker.

[20] During periods of mandate and tax policies, the unconditional level of crude oil volatility is 2.17% and 2.15%, respectively.

5 | CONCLUSIONS

Taking advantage of recent advances in timely assessments of volatility spillovers (Fengler & Herwartz, 2018) we quantify volatility spillovers among selected agricultural markets and crude oil at different market aggregation layers and for specific timeframes. We analyze volatility transmissions for two groups of commodities. Besides crude oil, considered systems include corn, wheat, and sugar feedstocks (ethanol system) or soybean, rapeseed, and palm (biodiesel system).

In general, food–oil linkages were weaker prior to the recent turbulent periods at food and financial markets, that is, between 1995 and 2005. Thereafter, sector-wide average crude oil volatility transmissions account for 16% (20%) of price uncertainty in grains and sugar (vegetable oils) markets (2006–2015). Besides binding biofuel policies (i.e., mandate or tax credit), crude oil volatility is an important determinant of uncertainties received by feedstock markets. The financial shocks of September 2008, May 2010 and August 2011 might have also exacerbated uncertainty in crude oil markets, further confounding transmission effects. Accordingly, in order to better elucidate the marginal effects of biofuel policies, we controlled for other market conditions. Throughout mandate enactments, our findings reveal more acute risk receptions from crude oil markets for ethanol compared with biodiesel feedstocks. Moreover, policy-induced volatility spillovers from crude oil to agricultural markets are 12% stronger for binding tax credit regimes (de Gorter et al., 2015).

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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APPENDIX

TABLE A1 Review of recent contribution to food–oil linkages

Article	Prices	Period	Method	Main findings
1. Algieri (2014)	USA	2005–2013, daily	MGARCH	Lagged crude oil and ethanol returns have a significant influence on corn, wheat, sugar, and soybean volatilities.
2. Wu and Li (2013)	China	2003–2012, weekly	MGARCH	Volatility spillovers from crude oil to corn and ethanol markets, but bidirectional spillovers between corn and ethanol.
3. Serra and Gil (2012)	USA	1990–2010, monthly	MGARCH	Stock forecasts lower corn volatility. Interest rate uncertainty increases it. Ethanol volatility spills over to corn volatility; stocks and interest rate treated as exogenous in variance equation.
4. Trujillo-Barrera et al. (2012)	USA	2006–2011, weekly	MGARCH	Volatility transmission from crude oil to corn and ethanol markets, as well as from corn to ethanol.
5. Alom et al. (2011)	Asia-Pacific	1995–2010, daily	MGARCH	Mean and volatility spillovers from crude oil to food.
6. Serra (2011)	Brazil	2000–2009, weekly	MGARCH	Shocks in crude oil and sugar markets increase ethanol volatility. No long run relation between crude oil and sugar prices. Ethanol does not affect either sugar or crude oil volatilities.
7. Serra, Zilberman, and Gil (2011)	Brazil	2000–2008, weekly	MGARCH	Crude oil volatility spillover to sugar and ethanol volatilities. Bidirectional spillovers between ethanol and sugar.
8. Serra et al. (2011)	USA	1990–2008, monthly	MGARCH	Crude oil volatility spillovers to ethanol, and to corn through ethanol.
9. Wu et al. (2011)	USA	1992–2009, weekly	MGARCH	Volatility spillovers from crude oil to corn spot and futures.
10. Chang and Su (2010)	USA	2000–2008, daily	MGARCH	Volatility spillovers from crude oil to corn and soybean (2004–2008); crude oil treated as exogenous in mean equation.
11. Zhang et al. (2009)	USA	1989–2007, weekly	MGARCH	Bidirectional volatility spillovers between corn and soybean. From soybean to ethanol only during 2000–2007.
12. Mensi et al. (2014)	USA, EU	2000–2013, daily	MGARCH and DCC	Crude oil volatility spillovers to corn. Gasoline volatility spillovers to corn, sorghum, and barley volatilities.
13. Gardebroek and Hernandez (2013)	USA	1997–2011, weekly	MGARCH and DCC	Volatility spillovers from corn to ethanol prices, but no major cross-market volatility effects between crude oil and corn.
14. Busse et al. (2011)	EU	1999–2009, daily	DCC	Significant correlations between crude oil volatility and both rapeseed oil and soybean volatility.
15. Nazlioglu et al. (2013)	International	1986–2011, daily	Granger causality in variance	Volatility spillovers from wheat to crude oil (1986–2005). Bidirectional causalities between crude oil and soybean, crude oil, and wheat (2006–2011).
16. Kaltalioglu and Soytas (2011)	International	1980–2008, monthly	Granger causality in variance	No volatility spillovers from crude oil to food and agricultural raw materials.
17. Harri and Hudson (2009)	USA	2003–2009, daily	Granger causality in variance	Volatility spillovers from crude oil to corn after the food crisis.
18. Liu (2014)	USA	1994–2012, daily	Cross correlation	Highly significant and persistent cross correlations between the volatilities of crude oil and each of the considered cereals.
19. Qiu et al. (2012)	USA	1994–2010, monthly	Structural VAR	Demand and supply shocks are the main volatility causes for price volatility in agricultural markets.
20. Balcombe (2011)	International	Various	Random parameter	Volatility spillovers from crude oil to the considered agricultural products.
21. Du, Yu, and Hayes (2011)	USA	1998–2009, weekly	Stochastic volatility	Volatility spillovers from crude oil to corn and wheat. Increased correlations between crude oil and corn, crude oil and wheat (2006–2009).
22. Alghalith (2010)	Trinidad and Tobago	1974–2007, annual	Nonlinear OLS	Increase of crude oil price and volatility yields higher food prices, while an increase in crude oil supply reduces them.

Note: Studies are clustered according to the method employed and ordered with respect to their date of publication.

TABLE A2 QML estimates of the BEKK model in (2)

	Ethanol				Biodiesel			
Matrix C								
Estimates	2.433	0	0	0	4.162	0	0	0
	−0.318	2.365	0	0	0.668	2.443	0	0
	−0.522	−0.735	3.572	0	−0.439	0.730	1.716	0
	0.889	−0.175	0.118	−1.128	1.454	1.388	1.278	−0.028
QML *t*-ratios	3.252	0	0	0	0.968	0	0	0
	−0.740	6.782	0	0	0.395	0.734	0	0
	−1.168	−0.520	2.518	0	−0.069	0.298	0.330	0
	1.677	−0.432	0.450	−1.545	1.711	0.427	0.571	−0.048
Matrix F								
Estimates	0.190	0.001	−0.010	0.025	0.265	0.028	−0.012	0.026
	−0.006	0.205	−0.059	−0.011	−0.074	0.171	−0.137	0.001
	0.004	−0.032	0.325	0.014	−0.022	−0.019	0.316	0.013
	0.026	−0.012	0.012	0.156	0.101	0.043	−0.014	0.237
QML *t*-ratios	5.498	0.137	−0.929	1.016	1.513	0.486	−0.089	1.188
	−0.329	10.459	−1.581	−0.674	−0.816	1.048	−0.910	0.009
	0.259	−1.627	3.967	1.125	−0.228	−0.706	0.807	0.611
	1.185	−0.613	0.509	3.748	1.428	0.482	−0.099	6.351
Matrix G								
Estimates	0.976	0.002	0.004	−0.007	0.946	−0.013	0.011	−0.012
	0.002	0.962	0.024	0.003	0.026	0.971	0.015	−0.009
	0.002	0.022	0.927	−0.003	−0.007	0.009	0.943	−0.014
	−0.005	0.003	−0.002	0.986	−0.031	−0.011	0.011	0.966
QML *t*-ratios	100.296	0.519	1.297	−0.969	12.217	−0.470	0.170	−0.920
	0.238	96.797	1.150	0.668	0.772	14.396	0.283	−0.186
	0.326	1.391	21.696	−0.521	−0.081	0.405	5.125	−0.685
	−0.757	0.795	−0.423	115.003	−1.007	−0.609	0.222	79.133

Note: Estimates of matrix C have to be divided by 1,000.